Socioeconomic and Racial/Ethnic Disparities in Cognitive Trajectories among the Oldest Old: The Role of Vascular and Functional Health

by

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ABSTRACT

Identifying modifiable causes of chronic disease is essential to prepare for the needs of an aging population. Cognitive decline is a precursor to the development of Alzheimer's and other dementing diseases, representing some of the most prevalent and least understood sources of morbidity and mortality associated with aging.

To contribute to the literature on cognitive aging, this work focuses on the role of vascular and physical health in the development of cognitive trajectories while accounting for the socioeconomic context where health disparities are developed. The Assets and Health Dynamics among the Oldest-Old study provided a nationally-representative sample of non-institutionalized adults age 65 and over in 1998, with biennial follow-up continuing until 2008. Latent growth models with adjustment for non-random missing data were used to assess vascular, physical, and social predictors of cognitive change.

A core aim of this project was examining socioeconomic and racial/ethnic variation in vascular predictors of cognitive trajectories. Results indicated that diabetes and heart problems were directly related to an increased rate of memory decline in whites, where these risk factors were only associated with baseline word-recall for blacks when conditioned on gender and household assets. These results support the vascular hypotheses of cognitive aging and attest to the significance of socioeconomic and racial/ethnic variation in vascular influences on cognitive health.

The second substantive portion of this dissertation used parallel process latent growth models to examine the co-development of cognitive and functional health. Initial word-recall scores were consistently associated with later functional limitations, but baseline functional limitations were not consistently associated with later word-recall scores. Gender and household income moderated this relationship, and indicators of lifecourse SES were better equipped to explain variation in initial cognitive and functional status than change in these measures over time.

Overall, this work suggests that research examining associations between cognitive decline, chronic disease, and disability must account for the social context where individuals and their health develop. Also, these findings advocate that reducing socioeconomic and racial/ethnic disparities in cognitive health among the aging requires interventions early in the lifecourse, as disparities in cognitive trajectories were solidified prior to late old age.

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CHAPTER 1: INTRODUCTION

Studies of health dynamics among older adults are conducted in a number of separate disciplines, with similar questions being asked, but from perspectives that employ vastly different assumptions about the antecedents of change in health among the elderly. The study of cognitive aging is a topic of great interest in many fields, yet integration of findings across these diverse sources is often not existent. Whether focusing on the relationship between cognitive health and co-morbid chronic diseases, represented most clearly in biomedical research, or examining how cognitive trajectories are associated with socioeconomic status (SES) and race/ethnicity, a common undertaking of social epidemiologists and social gerontologists, these often divergent areas of study can be incorporated to produce new insights into how cognitive health in aging adults is inter-related with both co-occurring chronic diseases and multiple levels of the social context.

The central goal of this dissertation is to provide evidence of how cognitive trajectories among the oldest Americans are associated with health in other body systems, and how this relationship is influenced by access to socioeconomic resources and race/ethnicity. To address this central question, the Asset and Health Dynamics among the Oldest Old (AHEAD) study provides a source of longitudinal observation that allows examination of the relationship between cognitive decline, co-morbid chronic diseases, SES developed across the lifecourse, and race/ethnicity. Cognitive trajectories, as measured by a summation of immediate and delayed word-recall scores, are examined using latent growth models (LGMs) designed to examine change over time with adjustment for covariates, while accounting for the presence of non-random missing data (referred to throughout as not missing at random or NMAR). I will define the core research questions to be addressed and give a brief description of the statistical approaches that were utilized to examine each research question.

Research Questions

Research question 1. The first goal of this project was to model cognitive trajectories of aging Americans using differing approaches of addressing NMAR data, and this is presented in Chapter 3. This portion of the dissertation does not explicitly examine disparities in cognitive decline, but rather compares results produced by multiple missing data models to determine how the varying assumptions and modeling strategies represented by each approach can impact the measurement of cognitive decline. Models for handling NMAR data rely on un-testable assumptions and require the use of sensitivity analyses that compare parameter estimates between the NMAR models that have substantially different assumptions. To begin this piece, an unadjusted LGM was estimated as a baseline model, and this was compared to a number of models designed to handle NMAR data. Next, a small set of covariates was used to produce parameter estimates across the traditional LGM and the NMAR models, providing evidence of how the estimation of covariate effects differ across these models.

One approach to handling data NMAR in growth modeling incorporates a sub-model that assesses the probability of missing data at each wave of measurement (Enders 2010). The models that were included in analyses that employ this NMAR strategy were the Wu and Carroll (WC) selection model and the Diggle-Kenward (DK) selection model. These models are similar in that they both incorporate logistic regression estimates of mortality into weighting of the LGM, yet each does so with differing assumptions regarding the values and trajectories of the outcome variable of interest. The second approach to controlling for the impact of NMAR data can be likened to a latent class analysis of missing data patterns. In pattern mixture modeling, LGMs are estimated separately for each unique missing data pattern with the pattern-specific estimates usually being combined as a weighted average that represents the population growth trajectory (Enders 2010). By comparing the results of each of these approaches to modeling cognitive decline among aging Americans, this research question provides an example of how NMAR models are implemented, how these models differentially weight observations based on missing data, and finally, how these models influence the estimation of cognitive trajectories, as well as the multiple predictor variables of interest.

Research question 2. Multiple investigations of cognitive decline coming from biomedical literature focus on the role of vascular diseases and their risk factors (VDRFs) in cognitive health among the elderly. The vascular hypothesis of cognitive aging proposes that cardiovascular and cerebrovascular disease, including coronary heart disease and stroke, and risk factors for cardiovascular disease including hypertension and diabetes affect frontal system cognitive functions, resulting in vascular cognitive impairment (VCI; Spiro and Brady 2008). A great deal of research supports this hypothesis, but the majority of these studies overlook the social context where cognitive and vascular health are developed. Most of the studies in this area do include measures of SES, but these are usually fragmentary measures un-able to capture how SES across the lifecourse contributes to the development of health in older adults. Furthermore, these studies usually include controls for race/ethnicity, but do not examine racial/ethnic variation in the influence of SES on cognitive trajectories. What biomedical studies of the vascular hypothesis fail to appreciate is the potential for lifecourse SES and race/ethnicity to account for the observed relationship between VDRFs and cognitive outcomes, as well as the potential for SES and race/ethnicity to moderate the relationship between cognitive and vascular health.

To contribute to the literature examining the role of cardiovascular risk factors on cognitive aging, Chapter 4 describes a study of the relationship between memory trajectories, diabetes, hypertension, and heart problems, focusing on the socioeconomic and racial/ethnic context where health is developed. Latent growth models with adjustment for NMAR data were employed separately for white and black respondents, and multiplicative relations between indicators of cardiovascular health and lifecourse SES were examined. This study provides a critical evaluation of the vascular hypothesis, using both rigorous statistical methods and robust controls for lifecourse SES. The results can inform the biomedical community on the centrality of lifecourse SES and race/ethnicity in estimating the influence of VDRFs on trajectories of cognitive health, and provide social gerontologists an understanding of how vascular health conditions can contribute to cognitive trajectories among the oldest Americans.

Research question 3. A great deal of research has shown a consistent relationship between cognitive and functional health, and evidence suggests that these health processes exert mutual influence upon one another across time. The bulk of existing studies on the interrelation of cognitive and functional health utilize cross-sectional samples, or create categorical thresholds of cognitive and functional health that are used to identify change in these measures over time, reducing the ability to estimate the amount and dynamics of change in each dimension of health. Without accounting for the unobserved prior causes that influence baseline levels of cognition and functional health in tandem, assessments of how baseline cognition influences change in functional limitations across time, and vice-versa, may be biased by the omission of the initial relationship between these variables. Similarly, socioeconomic variation in baseline cognitive and functional measures may be quite different from socioeconomic variation in change in these processes over time. Accounting for socioeconomic variation in baseline measures of cognition and physical function allows a more accurate estimation of how initial levels of these measures influence change in these outcomes over time. Also, including socioeconomic adjustments to the initial levels of each health process, as well as their trajectories of development, provides insight into socioeconomic disparities in initial measures of cognitive and functional health. The final goal is to provide guidance towards possible points of intervention that can help reduce the severity of change in these measures across time.

Chapter 5 presents research that assessed the co-development of cognitive and functional health trajectories. Once a structural model of the relation between cognitive and functional trajectories was developed, socioeconomic variation in the relationship between cognitive and functional health was examined. Change in functional limitations over time was regressed on interactions between the adjusted measures of baseline cognition and indicators of lifecourse SES, and this task was also undertaken for the path between baseline functional health and change in cognition. This process sheds light on how lifecourse SES may moderate the relationship between cognitive and functional health, and provides evidence of socioeconomic disparities in aging produced through the interlocking nature of cognitive and functional health outcomes in aging adults.

CHAPTER 2: BACKGROUND

The health and population dynamics of older Americans receives a tremendous amount of attention from scientists of many disciplines, and rightfully so: estimates predict that in 2050, the percentage of U.S. citizens age 65 and over will increase from around 13% in 2010 to nearly 21% of the entire population, with the percentage of adults age 85 or older jumping from 2% to 5% (Alwin, McCammon, Wray, and Rodgers 2008). Population aging is a global phenomena, with the global number of adults age 65 and over expected to double between 2006 and 2030 (Dobriansky, Suzman, and Hodes 2007). With the reduction of sickness and death attributable to infectious diseases, the graying of modern societies is accompanied by an increasing burden of chronic disease in the lives of older adults. Chronic diseases are the leading causes of morbidity and mortality in the United States, and will inevitably place an increasing weight on the economic and social systems responsible for supporting the health of older adults. Cognitive impairment related to Alzheimer's and other dementing diseases represents one of the costliest, and least understood, chronic diseases associated with aging.

Alzheimer's disease represents the sixth leading causes of death in the US, with around 5.5 million Americans living with Alzheimer's, and somewhere from 10 to 20 percent of adults age 65 and over displaying mild cognitive impairment (Farran et al. 2011). In 2007, around $21 billion in Medicaid costs and $91 billion in Medicare costs were associated with the care for adults with Alzheimer's and other forms of dementia (Farran et al. 2011). The majority of the population with Alzheimer's live at home, placing financial and care burdens on unpaid caregivers who support the needs of those with cognitive impairments. The unpaid care provided by caregivers for those with Alzheimer's was estimated to be worth $89 billion dollars in 2007, with businesses losing $36.5 billion due to the lost productivity of those caring for family or friends with Alzheimer's and other forms of cognitive impairment (Farran et al. 2011). Identifying early warning signs of cognitive impairment and potentially modifiable predictors of cognitive decline is crucial to reducing the growing personal and public costs associated with cognitive diseases among the aging.

The search for consistent and modifiable antecedents to cognitive decline occurs within a number of specialized fields of research. Addressing this issue from a biomedical perspective, vascular and functional health have been widely explored as two potential precursors to the onset of cognitive decline (Bowler 2005; Duron and Hanon 2008, Farmer et al. 1987, McGuire, Ford, and Ajani 2005; Moritz, Kasl, and Berkman 1994; Moody-Ayers et al. 2005). Attending to the social risk factors for cognitive decline, low socioeconomic status (SES) has been consistently associated with increased risk for rapid cognitive decline and developing Alzheimer's and dementia in old age (Alley, Suthers, and Crimmins 2007; Cagney and Lauderdale 2002; Lee, Kawachi, Berkman, and Grodstein 2003). Also, variation in cognitive health has been attributed to the social disadvantages associated with status as a racial/ethnic minority (Black and Rush 2002; Lyketsos, Chen and Anthony 1999; Schwartz et al. 2004). These different approaches to examining predictors of cognitive change offer their own insights into the nature of cognitive change and its antecedents, yet the integration of these perspectives has yet to develop an understanding of how the biological and social precursors of cognitive change may be inter-related.

To contribute to the integration of social and biological inputs to cognitive change among older adults, this chapter provides a review of previous work that has examined the relationship between social and biomedical risk factors for cognitive decline. Specifically, this review discusses the study of cognitive aging, the relationship between SES and cognitive decline, as well as describes work that has explored how vascular and physical health may be associated with cognitive aging. This review provides the sociological grounding for the substantive examination of vascular predictors of cognitive health presented in Chapter 5, and the co-development of cognitive and functional health trajectories presented in Chapter 6.

Defining Cognitive Aging

In attempting to understand the nature of cognitive abilities, researchers tend to define cognition as composed of both fluid and crystallized abilities (Cattell 1971; Alwin and Hoffer 2008). Fluid cognitive abilities are related to complex problem solving and abstract reasoning, where crystallized abilities are developed through the experience of utilizing fluid abilities in culturally defined tasks. As crystallized abilities are the product of investments in time and effort across the lifecourse, these cognitive abilities based on experience and reason tend to remain consistent throughout old age. Fluid abilities, being the product of perceptual speed, working memory, and logical problem-solving, reach their highest point early in life and steadily decrease with age. Fluid abilities represent those cognitive processes that decline most rapidly with age (Small et al. 1999), and are therefore the point of focus for the majority of research on cognitive aging.

In their interdisciplinary text on cognitive aging, Alwin and Hofer (2008) suggest that the study of cognitive aging is usually conducted through perspectives that are either psychological, biological, or sociological. Psychological theories emphasize an underlying psychological cause of cognitive aging, including explanations such as the generalized slowing of processing abilities (Salthouse 1996). Biological theories of cognitive aging focus on the integrity of neurological structure and related organ function, reducing cognitive function directly, or through health problems in other body systems (Spiro and Brady 2008; Waldstein 2000). Approaching cognitive aging as a product of social mechanisms, sociological theories posit that changes in cognitive function can be attributed to disabilities, restricting participation in everyday social activities, or through the accumulation of disadvantage over time (Dannefer 2003; Ross and Wu 1996). While distinct in their approaches to understanding the causes of cognitive aging, these perspectives are complimentary, and in combination, can produce novel insights into the nature of cognitive decline and its antecedents. The research presented in this dissertation integrates the biomedical and sociological perspectives of cognitive aging, aiming to understand how the interrelation of biological health interacts with access to socioeconomic resources across the lifecourse to predict individual-level change in cognitive functioning.

Linkages between Health and Social Conditions

It is commonly accepted that those with lower levels of socioeconomic resources have worse health outcomes than those with higher levels (Davey-Smith 1997; Lynch and Kaplan 2000). Differential access to health-enabling resources is considered a fundamental cause of disparities in health outcomes (Link and Phelan 1995, 2000, 2005), and the resources Link and Phelan refer to are various forms of economic, social, and cultural capital that embed individual health within a larger socio-cultural context. Socioeconomic status (SES) refers to a varied set of social and economic indicators that represents one's access to resources, which varies and accumulates across the lifecourse. Lynch and Kaplan (2000) weigh the relative contributions of traditional indicators of SES including education, occupation, and income in relation to health, suggesting the inclusion of a wider variety of resources. Socioeconomic status unfolds dynamically across the lifecourse and social chains of risk extend from childhood to late old age (Kuh, Power, Blane, and Bartley 1997). The concept that variations in exposure to SES in early life produces divergent health outcomes in older ages is defined as the theory of cumulative disadvantage (Ross and Wu 1996), and is a central tenant of the lifecourse approach to social epidemiology (Berkman and Kawachi 2000). Those who enjoyed high SES in childhood are more likely to have favorable SES in adulthood (Johnson and Reed 1996) as well as experience better health in adulthood (Haas 2007; Rahkonen, Lahelma, and Huuhka 1997). This research integrates measures of SES captured in late adulthood with retrospective measures of childhood socioeconomic circumstances, attempting to measure one's ability to access health-enabling resources across the lifecourse.

Both health and SES are associated with race/ethnicity. Minorities experience illness earlier and more severely than their white counterparts, and experience mortality due to illness more often than whites (Williams et al. 2010). Race and SES are inter-locking characteristics (Navarro 1990, Williams and Collins 1995) and indicators of SES can have substantially different meaning for individuals from differing racial/ethnic backgrounds, meaning crude measurements of SES can produce biased estimates of racial differences in the outcome of interest (Adler and Rehkopf 2008). By adjusting for a varied set of socioeconomic indicators, the effects of race/ethnicity on health not captured by SES are more likely to be evident.

Social determinants of cognitive health. Substantial evidence links SES and race/ethnicity to cognitive health among the aging. Previous studies of the relationship between SES and cognitive decline have tended to focus on education as the key indicator of SES. Education has been consistently related to cognitive health outcomes among the elderly (Alley, Suthers, and Crimmins 2007; Cagney and Lauderdale 2002; Lee, Kawachi, Berkman, and Grodstein 2003). The relationship between education and cognitive aging is complex as education can be an indicator of both SES as well as a marker of years spent developing and exercising cognitive abilities (Cagney and Lauderdale 2002). In studies with robust controls for SES including lifetime wealth and current income, the impact of education on cognitive function remains strong (Cagney and Lauderdale 2002; Lee, Kawachi, Berkman, and Grodstein 2003).

Studies exploring the impact of SES on cognitive aging have tested indicators of SES including lifetime wealth, current income, and occupation, in addition to indicators of childhood SES. Cagney and Lauderdale (2002) found lower cognitive function among whites with low income and assets, but these relationships did not hold for blacks or Hispanics. Lee and colleagues (2003) reported increased odds of cognitive decline among women whose fathers were farmers compared to white-collar workers, but household income was not statistically significant. Exploring the relationship between childhood SES and cognitive decline, Faul (2008) found that having comfortable childhood circumstances including high paternal education and occupational prestige was protective against cognitive decline among aging adults. Those with higher SES across the lifecourse consistently have better cognitive outcomes than those with low SES, and the nature of this relationship should vary for those with differing racial/ethnic characteristics.

Compared to work relating SES to cognitive decline, relatively little research exists on racial/ethnic disparities and cognitive aging. Racial/ethnic disparities in cognitive decline are typically attributed to inequalities in education and diseases that predict cognitive decline (Black and Rush 2002). With that said, cognitive disparities in late adulthood have been found when comparing blacks to other races in the face of controls for SES (Lyketsos, Chen, and Anthony 1999; Mehta et al. 2004; Schwartz et al. 2004).

Cognitive and Vascular Health in Socioeconomic Context

A great deal of research and deliberation has been aimed at assessing the influence of cardiovascular and cerebrovascular health on cognition among aging populations (Bowler 2005; Duron and Hanon 2008, Farmer et al. 1987, Speith 1964). The vascular hypothesis posits that cardiovascular and cerebrovascular disease, including coronary heart disease and stroke, and risk factors for cardiovascular disease including hypertension and diabetes (collectively referred to as vascular diseases and their risk factors [VDRFs]), affect frontal system cognitive functions, resulting in vascular cognitive impairment (VCI; Spiro and Brady 2008). Cardiovascular risk factors including hypertension and type II diabetes have been related to frontal system functions including verbal fluency and memory retrieval (Awad et al. 2004; Cuckierman, Gerstein, and Williamson, 2005; Spiro and Gaziano 2005). Myocardial infarction (MCI) and atherosclerosis are consistently found to increase the risk of Alzheimer's disease or vascular dementia (Aronson et al. 1990; Breteler 2000; Hofman et al. 1997). Vascular diseases and their risk factors influence cognition through restricted blood flow (hypoperfusion) to the brain (de la Torre 2004). Incorporation of these VDRFs into studies of cognitive aging help parse normal age related cognitive variance from non-normative cognitive decline associated with VDRFs, and VDRFs represent an important set of potentially modifiable risk factors for abnormal cognitive aging (Spiro and Brady 2008). In their review of VCI, Spiro and Brady (2008) call for increased collaboration between psychologists and biomedical researchers to better understand the vascular processes of cognitive aging. To contribute to the understanding of VDRFs and cognition among the elderly, a sociological perspective focused on the structural determinants of cardiovascular health and cognitive aging is essential to account for the social environment where aging and the development of cardiovascular and cognitive health occur.

A potentially confounding factor in the relationship between VDRFs and cognitive outcomes is the social context where both cognitive and vascular health is developed. Diabetes is nearly twice as common in blacks compared to whites (Brancati, Whelton, Kullerm, and Klag 1996; Smith 2007). When testing the relationship between race/ethnicity, SES, and diabetes, the odds of having diabetes for blacks is decreased to non-significance with numerous controls for SES, indicating that socioeconomic status is a stronger predictor of diabetes prevalence than race/ethnicity (Link and McKinlay 2009). While heart disease is the number one killer of both white and black Americans, multivariate analysis controlling for numerous health risk factors has shown that diabetes is the health indicator most closely related to mortality in blacks (Kuchibhatla and Fillenbaum 2002). Additionally, childhood and adult SES has been linked to heart disease in middle-age (Blane, Davey-Smith, and Hole 1996; Kaplan and Salonen 1990). Hypertension is more prevalent in black than white individuals (Ong et al. 2006) and low SES is associated with high blood pressure (Grotto, Huerta, and Sharabi 2008). Having low SES has also been associated with higher mortality from stroke, more stroke risk factors, and lower post-stroke quality of life (Kapral et al. 2002; van den Bos, Smits, and van Straten 2002). In conclusion, the prevalence of VDRFs and their influence on health and mortality vary across lines of SES and race/ethnicity, thus necessitating a focus on these contextual variables in any study of vascular hypotheses of cognitive aging.

In summary, vascular hypotheses of cognitive aging must account for socioeconomic and racial/ethnic variation in VDRFs if correct estimates of the relationship between vascular and cognitive health are to be established. This study takes the relationship between cognition, VDRFs, and social context seriously, examining variation in the relationship between trajectories of memory, VDRFs, and lifecourse SES separately for white and black respondents.

Physical and Cognitive Health in Socioeconomic Context

The disablement process provides a useful framework from which to understand the interrelation of cognitive and functional health trajectories. Conceptually, the disablement process describes the pathway between disease pathology and disablement, where pathologies create impairments in specific body systems that produce restrictions in basic abilities and actions (functional limitations), in turn restricting one's abilities to carry out activities essential to survival and social functioning (disability; Verbrugge 1994). Demographic, social, and behavioral risk factors contribute to the development of disability, and represent potential points of intervention aimed at reducing disability. Health problems develop along this main pathway directly, can be enforced through feedback effects on the given outcome, and finally can initiate and enforce the development and progression of other ailments. Concerning the measures of cognitive and functional health being analyzed here, both cognition and functional limitations are considered antecedents of disability that restrict one's ability to effectively carry out activities and essentially one's ability to survive (Verbrugge 1994). This work is specifically interested in the potential for a given health problem to influence the development of another health problem, and how social risk factors contribute to this relationship.

The relationship between cognitive and functional health has long been a focus in studies of health and aging, though these works tend not to examine the mutual influence that may occur in this relationship. The largest body of research supports the conclusion that cognitive functioning is associated with, and influences the development of, functional limitations and activity of daily living (ADL) limitations (McGuire, Ford, and Ajani 2005; Moody-Ayers et al. 2005; Moritz, Kasl, and Berkman 1994; Speirs et al. 2005; Stuck et al. 1999; Wang, van Belle, Kukull, and Larson 2002). The bulk of work in this area has focused on cross-sectional associations between cognition and functional limitations, though the longitudinal analyses support that cognition influences the development of functional limitations over time (Gill, Williams, Richardson, and Tinetti 1996; Moody-Ayers et al. 2005; Moritz, Kasl, and Berkman 1994; Speirs et al. 2005; Wang, van Belle, Kukull, and Larson 2002).

Much less work has investigated the concomitant development of cognitive and functional health, but existing research suggests that cognitive and functional health influence the development of one another over time. Atkinson et al. (2005) examined predictors of combined cognitive and physical decline in a female-only sample, finding that impairments in either cognition or instrumental activities of daily living (IADLs) predicted future decline in both processes.

Similarly, Black and Rush (2002) found that when controlling for sociodemographics and chronic health conditions, baseline disability and cognitive performance predicted concomitant decline in both dimensions of health. Both of these studies used logistic regression models to predict the appearance of combined cognitive and functional decline, and neither of the studies accounted for the potential multi-collinearity between cognitive and functional health that could potentially bias the coefficient estimates of cognitive and functional health being used as independent variables. Regardless, the few studies that examine the co-development of cognitive and functional decline provide support for further elaborations in this line of research.

The studies discussed provide compelling evidence of an association between cognitive and functional health, but to varying degrees, they overlook the role of SES in the association between these health processes. A number of the studies mentioned include controls for SES, but these are usually rudimentary measures that capture only a few dimensions of the socioeconomic context. Furthermore, no studies found explicitly examined the potential for SES to moderate the relationship between cognitive and functional health. For example, socioeconomic resources may protect an individual experiencing cognitive decline from increasing functional limitations in the future. Assistance from personnel or equipment designed to support an individual experiencing cognitive decline may reduce the risk of developing functional limitations. Likewise, those with limited access to socioeconomic resources across the lifecourse may be at greater risk of experiencing cognitive decline due to un-attended functional limitations than those with unrestricted access to these health-enabling resources. Study of the reciprocal relationship between cognitive and functional health necessitates an explicit focus on the socioeconomic context of aging.

Social predictors of functional limitations. Functional limitations have been shown to be associated with a number of socioeconomic indicators. Both education and income have been positively associated with physical functioning (Berkman et al. 1993; Guralink et al. 1993; Kaplan et al. 1993; Seeman et al. 1994), and disparities in disabilities based on education and income increased between 1982-2002 (Schoeni, Martin, Andreski, and Freedman 2005). Focusing on lifecourse SES, Haas (2008) found that in light of significant negative associations between functional limitations and adult SES, parents' education and childhood housing stability were both negatively associated with the development of functional limitations over time. Recent meta-analysis of studies examining functional health and childhood SES has substantiated these findings (Birnie et al. 2011). When examining the association between cognitive and functional trajectories, it is essential to adjust each of these trajectories for the effects of lifecourse SES.

DISCUSSION

Approaching cognitive aging from varied theoretical and methodological approaches is essential to prepare for the coming increase in older adults experiencing cognitive decline. A significant amount of work coming from biomedical science suggests that cognitive functioning among older adults is associated with, and in some cases predicted by, attendant VDRFs and functional health. These works focus on co-morbidities associated with cognitive decline, and highlight the interrelated nature of health in multiple body systems. From another perspective, cognitive aging has been consistently associated with the socioeconomic context in which individuals develop across their lifecourse. Access to socioeconomic resources is found to be a consistent predictor of cognitive health specifically, and overall health more generally, and may play an important role in how vascular and functional health effect cognitive aging. By examining how co-occurring chronic diseases and physical ability are related to cognitive trajectories in older adults, placing an emphasis on how all health outcomes are influenced by access to socioeconomic resources, this work aims to advance our understanding of cognitive health as a chronic disease with multiple related causes and potential points of intervention.

CHAPTER 3: METHODOLOGY

Researchers interested in measuring health dynamics over time and establishing temporal ordering between exposure to risk and later health outcomes rely on data provided by prospective longitudinal studies. In all longitudinal studies, follow-up of participants and high retention rates are crucial to maintaining an adequate sample of participants, and more importantly, to assure against biases introduced to the study caused by selective attrition and dropout. Particularly in longitudinal studies of aging, the phenomena of mortality selection threatens the accuracy and usefulness of measurements as likelihood of being present in later waves of the sample can be associated with the health outcomes of interest. Mortality selection can introduce bias into the estimation of causal effects (Glymour, Wueve, and Chen 2008), though if the outcome of interest declines with age but is positively related with longevity (e.g. cognitive functioning), the bias is actually a conservative underestimate of age-related decline (Alwin, McCammon, Wray, and Rodgers 2008). No matter the nature of bias introduced by mortality selection in the study of cognitive decline, accurate estimates of cognitive decline and its attendant risk factors are essential for the proper planning and implementation of policy that will best serve the needs of the growing population of older adults, and the budget constraints faced by modern economies.

Those utilizing longitudinal studies of health and aging must account for the presence of mortality selection, a phenomena that creates problems of missing data. Specifically, when the outcome variable of interest, in this case cognitive function, is related to the likelihood of dropout, which produces missing data, the missing data are considered not missing at random (NMAR; Enders 2011; Little and Rubin 2002; Rubin 1976). This is in contrast to missing data that may be associated with other variables in the multivariate analysis, but not related to the underlying value of the outcome variable, which is described as missing at random (MAR). When examining change over time in an outcome variable of interest, and the values of that outcome are related to the likelihood of missing data in the outcome variable, biased parameter estimates of the outcome and the effect of predictor variables on that outcome may result (Enders 2011). Statistical methods that attempt to address the presence of NMAR in studies utilizing latent growth models (LGMs) have previously been difficult to implement, but are now becoming available in common statistical packages. A major aim of this study was to implement these methods in a substantive examination of socioeconomic and racial/ethnic variation in cognitive trajectories, allowing an exposé of these models, their underlying assumptions, an understanding of how they influence measurement of socioeconomic and racial/ethnic in cognitive trajectories, and finally, the potential setbacks inherent in these methods.

As a study explicitly focusing on the health and socioeconomic status (SES) of Americans in the latest years of life, the Asset and Health Dynamics among the Oldest Old (AHEAD) study provides an un-paralleled opportunity to examine the substantive relationship between cognitive decline, SES developed across the lifecourse, and race/ethnicity. Furthermore, the influence of mortality selection in these relationships and the utility of statistical models designed to account for the potential biases produced by data NMAR are methodological issues that the AHEAD study allows the interested researcher to address. As a study explicitly focused on the oldest Americans, the AHEAD study exhibits a large amount of dropout, with the majority being caused by mortality. The loss of follow-up due to mortality is a methodological concern faced by all researchers analyzing longitudinal studies of aging, and the AHEAD study provides a great opportunity for the implementation of models designed to address the potential biases caused by mortality selection. Description of the AHEAD study and the specific variables that are utilized throughout this project is followed by presentation of the statistical methods used in examining the relationship between cognitive trajectories, co-morbid health indicators, and lifecourse SES, closing with a brief comparison of estimates provided by the NMAR models. This chapter provides a strong methodological footing for the following substantive chapters.

Analytic Sample Study Description

In the late 1980s, existing sources of data examining the aging US population were deemed inadequate, influencing the formation of a group of advisors for the National Institute of Aging (NIA), a component of the National Institute of Health (NIH), to recommend the development of a new long term study of aging focusing on the economic and social factors faced by modern aging adults (NIH 2007). With funding from NIA and direction from a number of investigators, the Institute of Social Research at the University of Michigan began the HRS in 1992. Currently, David Weir of the University of Michigan Population Studies Center directs the HRS.

Created as a national panel survey employing biennial assessment of America's aging population, the HRS began as a representative sample of the US population between ages 51-61 in 1992 (including spouses regardless of age; Hauser and Weir 2010). To supplement the HRS, the Asset and Health Dynamics among the Oldest Old (AHEAD) study began in 1993 as a spinoff of the HRS that focuses on Americans considered to be the oldest-old; birth cohorts born in 1923 or earlier, or who were 70 years of age or older in 1993 (Juster and Suzman 1995). Interviewees in the AHEAD sample were re-assessed in 1995, but in 1998, the HRS and AHEAD surveys were integrated to form a single study collectively known as the HRS. In addition to the HRS and AHEAD samples, a number of younger cohorts have become part of the HRS, including the "war babies" cohort born between 1942 and 1947, and the "baby boom" cohort, represented by "early Boomers" born between 1948 and 1953, and "mid Boomers", born between 1954-1959, which were incorporated into the 2010 HRS data collection. The following of early cohorts throughout the life cycle, and the continuing addition of new cohorts into the study, provide a rich source of data for researchers interested in the dynamics of health and aging in the US population.

To capture a representative sample of America's aging population, a multi-stage area probability sample design was used, with oversampling of key populations of interest including blacks, Hispanics, and Floridians. The HRS observational unit is considered an "eligible household financial unit", and the original sample excludes institutionalized persons (those residing in nursing homes, long-term or dependent care facilities, jails, and prisons), though individuals who move from the household population into these institutions continue to be followed (Health and Retirement Study 2008). The AHEAD study sample design is identical to that of the HRS sample design, other than the fact that the AHEAD study sampled two groups differentially, where younger households were interviewed by phone and older households were interviewed in person. Those interviewed by phone were chosen from two distinct sampling frames, with around 50% of the group being chosen from the original area probability sample and the remaining 50% from a stratified sample of Medicare enrollees. In 1992, the HRS had a response rate of 81.6%, and in 1993, the response rate for the entire AHEAD study was 80.4% (Health and Retirement Study 2008).

The HRS/AHEAD study has become a central tool in the work of population health and aging research. From 1992 to 2008, more than 30,000 respondents were interviewed at least once with more than 155,000 complete interviews (Hauser and Weir 2010). More than 1,400 papers have been published using data from the HRS and the HRS data has more than 10,000 registered users (Hauser and Weir 2010). In addition to the influence the HRS has had here in the US, the HRS has either directly or indirectly influenced the development of several international efforts to examine dynamics of population aging, including national studies in Mexico, England, South Korea, China, and India, as well as a consortium of studies harmonized with the HRS taking place in 16 countries (Survey of Health, Aging, and Retirement in Europe; SHARE).

To increase the accessibility of the HRS/AHEAD to researchers, the RAND Center for the Study of Aging, with funding from the NIA and Social Security Administration (SSA), has created a user-friendly version of a subset of the HRS/AHEAD (St. Clair et al. 2010). The RAND version of the HRS/AHEAD contains cleaned and processed variables, as well as imputations for missing data on a number of income and wealth variables. The latest version of the RAND HRS/AHEAD was used in this project (version J), and the RAND HRS/AHEAD measures were utilized whenever possible.

The analytic sections of this project utilize observations taken from the AHEAD study between 1998 and 2008. In 1998, the interview program was standardized for both HRS/AHEAD participants and a number of questions concerning childhood SES and health that were previously included in experimental modules were incorporated into the interview conducted on the entire sample. The analytic section of Chapter 4 utilizes a sample of AHEAD participants in 1998 restricted to participants who were either of white or black race/ethnicity and who had valid measures of immediate and delayed word-recall scores, leaving a sample of 3,979 white and 555 black participants (N = 4,534). The analytic sample in Chapter 5 is restricted to AHEAD participants in 1998 who were either of white, black, or Hispanic race/ethnicity, and who had valid measures on both immediate and delayed word-recall scores, and who had non-missing values on the scale of functional limitations under analysis. These restrictions yielded a sample of 3,885 white, 534 black, and 234 Hispanic participants (N = 4,653).

Dependent Variables

Word-recall scores. The central outcome variable of interest in this set of studies was the episodic memory tasks included in the AHEAD study, composed of immediate and delayed word-recall scores. The immediate word-recall task asked respondents to recall a list of 10 common nouns immediately after hearing them and delayed word-recall was measured after five minutes of test administration had passed. Factor analysis on the HRS cognitive tests has shown that immediate and delayed word-recall load on a single factor with an Eigenvalue greater than one (Ofstedal et al. 2005). This measure of cognitive functioning was selected as a sensitive measure of cognitive change (Small et al. 1999).

Functional limitations. In the examination of the co-evolution of cognitive and functional health trajectories (Chapter 5), the key indicator of functional limitations was a summation of 11 indicators of limitation in functional mobility (Nagi 1969; Rosow and Breslau 1966). Respondents were asked if they had difficulty in each of the following activities: stooping or crouching, climbing one flight of stairs without resting, climbing several flight of stairs without resting, moving large objects, sitting in a chair for two hours, getting up from a chair after sitting for long periods, lifting weights over 10 pounds, raising arms above shoulder level, walking one block, walking several blocks, and picking up a dime from a table (1 = yes; 0 = no). Respondents with 7 or more missing values on these 11 items were coded as missing. Although the construction of the functional limitations composite score does introduce error by assuming that those with one through three missing values actually had a zero for the given missing value, this setback was determined to be less detrimental than the exclusion of the approximately 1,300 participants who had one through three missing values on the individual items used to create the functional limitations summary. The mobility functional limitation measure was chosen as the most advantageous indicator of functional health, as compared to other popular measures including Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs), as this measure of functional limitation minimizes the influence of social and environmental factors on the underlying physical ability of the participant (Haas 2008). This measure has been found to have good reliability (Cronbach's alpha = .85; Fonda and Herzog 2004).

Independent Variables

Vascular diseases and their risk factors. Analyses in Chapter 4 examined the relationship between cognitive trajectories and vascular diseases, utilizing self-reported measures of being diagnosed with a number of vascular diseases and their risk factors (collectively referred to as VDRFs). Measures of VDRFs included were self-reported diagnosis of heart problems, high blood pressure, diabetes, and stroke. Regarding heart problems, participants were asked if they had been told by a doctor they had coronary heart disease, angina, congestive heart failure, had had a heart attack, or other heart problems (1 = yes, 0 = no). Participants were also asked if they had been told by a doctor they had high blood pressure or hypertension (1 = yes, 0 = no), had diabetes or high blood sugar (1 = yes, 0 = no), and if they had had a stroke (1 = yes, 0 = no).

Socioeconomic status and race/ethnicity. As socioeconomic and racial/ethnic variation were central to this investigation of health and cognitive aging, care was taken to include a robust set of indicators capturing access to socioeconomic resources across the lifecourse. The racial/ethnic groups examined in this study included non-Hispanic whites, blacks, and Hispanics. The study of vascular and cognitive health presented in Chapter 4 compares the influence of lifecourse SES on the relationship between VDRFs and memory trajectories for whites and blacks, examining the estimates of VDRFs and lifecourse SES separately by race/ethnicity. In the Chapter 4 analyses, the Hispanic portion of the AHEAD sample was too small to produce reliable estimates for all of the predictor variables and was excluded. Examination of the co-evolution of cognitive and functional trajectories described in Chapter 5 included non-Hispanic white, black, and Hispanic participants, using white respondents as the reference group.

Education, longest occupation tenure, household income, and household assets were used as measures of SES in adulthood, although measures of occupation, income, and assets were chosen for their representation of the accumulated exposure to socioeconomic resources across the lifecourse. Education was measured as the number of years of education accumulated by each participant. The investigation of vascular and cognitive health in Chapter 4 examined education as a continuous variable, where the investigation of trajectories of cognitive and physical health in Chapter 5 utilized education as a set of three dummy codes representing less than high school (0-11 years), high school graduates (reference group), and those with more than 12 years of education. Occupation was measured as the job with longest reported tenure, capturing the social and environmental characteristics of the occupation in which each respondent spent the greatest amount of their working life. Individuals who reported their longest employment tenure as professional/technical workers, managers, officials or proprietors, clerical and kindred workers, and those in sales were defined as white-collar workers. Individuals reporting longest employment tenure as craftsmen, foremen, operators, laborers, service workers or farmers were labeled as blue-collar workers. A dummy variable was included to capture the work experience of females who reported fewer than 4 years of lifetime work experience and who self-identified as a homemaker. A final category was created for individuals whose work experience did not fall within the previously defined categories. In all analyses, white-collar workers were used as the occupational reference group.

Household income and household assets were analyzed as summary measures of numerous sources of income and asset holdings included in the RAND HRS/AHEAD data (version J; St. Clair et al. 2010). Household assets were measured as a summary of the net value of the respondent's primary residence, all real estate holdings (excluding secondary residence), vehicles, businesses, IRA and Keogh accounts, all stocks, mutual funds, and investment trusts, checking, savings, or money market accounts, CDs, government savings bonds, and T-bills, bonds and bond funds, and all other savings, minus debts owed on mortgages, home loans, and other sources of debt. Household income was measured as the total household income of the respondent and their spouse, including individual earnings, income from Social Security (disability, Supplementary Security, and retirement), unemployment or workers compensation, income from other government transfers, and other sources of income.

Household income and assets were transformed on a log scale to reduce the right-skew in these variables. Both income and net assets were natural-log adjusted to account for a positively skewed sample distribution. Due to the inclusion of debt in the assets variable as well as zero values in the income variable, $100 was added to every observation to allow for correct log transformation. In addition, absolute values of the assets variable that included debt were logged, and then transformed back to their original direction.

Measures of childhood SES were included to capture respondents' access to socioeconomic resources beginning in the first years of life. Parents' education, self-reported childhood circumstances, and father's occupation were analyzed in the set of studies presented here. Mother's and father's education were measured separately using a dummy indicator representing whether each parent had attained 8 or more years of education, and this coding was utilized in both analytic sections incorporating covariates. Respondents were asked what their father's occupation was when the respondent was age 16. Father's occupation was coded as white-collar or other occupational status (1 = white-collar, 0 = other occupation), and again, this coding scheme was used in both analytic portions of this project. Finally, a retrospective assessment of whether the respondent's family had favorable childhood circumstances (non-poor) was included only in the examination of VDRFs and cognitive trajectories. This measure was not included in the analytic section of Chapter 5 to reduce the number of variables in the complex models utilized in that section of the dissertation.

Control variables. Demographic controls were included to provide a more accurate analysis of the relation between cognitive performance, SES, and vascular and functional health outcomes. Analyses controlled for gender and the respondent's age at initial interview. Marital status at time of initial interview was included to control for possible associations between health and marital status, with those reporting being married, married with spouse absent, or partnered being defined as married, and those reporting being separated, divorced, widowed, or never married defined as un-married.

Table 1 presents descriptive statistics for all variables used in the examination of vascular inputs to cognitive health found in Chapter 4, and Table 2 provides descriptive statistics for all variables utilized in examining the co-evolution of cognitive and functional health presented in Chapter 5.

Statistical Modeling of Cognitive Trajectories with Non-Random Missing Data

Mplus version 6.1 (Muthén and Muthén 2010) was used to produce all statistical models utilized in this study, and provided the capacity to implement a number of innovative approaches to addressing issues of missing data. After discussing the core of the statistical models that will be utilized throughout this study, problems of missing data on both outcome and predictor variables, and how Mplus can be used to counter these issues, will be addressed.

Latent growth modeling. Latent growth modeling (LGM) is considered a special case of structural equation modeling (SEM), where the measured outcome variables are repeated measures of the same variable *y* (Preacher, Wichman, MacCallum, and Briggs 2008). Conceptualization of the modeling process requires initial definition of the latent growth model. First, the unconditional growth model predicts y_{it}, or the value of the trajectory variable y for the ith case at time t:

$$y_{it} = \alpha_i + \lambda_t \beta_i + \varepsilon_{it}$$

where α_i is the random intercept for case i, λ_t represents the time-trend variable, β_i is the random slope for case i, and ε_{it} is the error term for each individual i and each time t (Bollen and Curran 2006). The intercept equation for the model represents the individual intercept α_i as a function of the mean intercepts for all cases μ_α and an error disturbance term $\zeta_{\alpha i}$. The slope equation represents the individual slope β_i as a function of the average slope for all cases μ_β and an error disturbance term $\zeta_{\beta i}$ (Bollen and Curran 2006):

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i}$$

$$\beta_i = \mu_\beta + \zeta_{\beta i}$$

The previous equations are brought together to form the combined model, or the reduced-form equation of the trajectory model (Bollen and Curran 2006):

$$y_{it} = (\mu_\alpha + \lambda_t \mu_\beta) + (\zeta_{\alpha i} + \lambda_t \zeta_{\beta i} + \varepsilon_{it})$$

To create a model conditional on the effects of covariates, the intercept and slope equations are modified to incorporate the effects of covariates x_i, where α_i and

β_i now represent the mean intercept and slope when x_i equals 0 (Bollen and Curran 2006):

$$\alpha_i = \mu_\alpha + \gamma_{\alpha i} x_{1i} + \zeta_{\alpha i}$$

$$\beta_i = \mu_\beta + \gamma_{\beta i} x_{1i} + \zeta_{\beta i}$$

This modification is represented in the reduced-form model as follows:

$$y_{it} = (\mu_\alpha + \lambda_t \mu_\beta) + (\gamma_\alpha + \lambda_t \gamma_{\beta 1}) x_{1i} + (\zeta_{\alpha i} + \lambda_t \zeta_{\beta i} + \varepsilon_{it})$$

Figure 1 provides a diagram of an un-conditional latent growth model. Note that the factor loadings are omitted to reduce clutter in the diagram. All factor loadings on the latent intercept are constrained to a constant value of 1, indicating the constant level of the outcome if there were no growth. Factor loadings on the latent slope would range from 0 to 8, increasing in intervals of 2 to match the 2-year increment between measurements.

Missing data. Mplus provides a useful suite of tools to account for multiple forms of missing data. Multiple imputation was used to account for missing data in predictor variables (20 datasets were imputed and analyzed, utilizing all predictor variables included in each of the models presented in Chapters 4 and 5, as well as the baseline values of word-recall [Chapter 4 and Chapter 5] and initial values of functional limitations [Chapter 5]). The imputation algorithm was allowed to cycle for 30,000 iterations, and data was saved at every 300th step (Enders *N.d.*). The sample utilized in Chapter 4 had only one variable with more than 10% missing data (doctor diagnosed heart problems = 10.23% missing) and in the sample used in Chapter 5, two variables had greater than 10% missing data; father's education > = 8 years = 10.12% missing; father white-collar occupation = 13.54%). All descriptive statistics and parameter estimates reflect averages across the 20 imputed datasets.

The use of multiple imputation requires the specification of interactive effects prior to the imputation process. All interactions examined in Chapter 4 were created prior to imputation, where all continuous variables were mean-centered, and the interactive term was a product of multiplying the two direct effects of interest. All interactions examined in Chapter 5 were the product of the multiplication of an observed variable and the estimated individual intercept (latent variable) of either word-recall or functional limitations. The latent variables included in the interaction were mean-centered, and all continuous observed variables were centered prior to creation of the interaction term. The product for the observed by latent variable interactions could not be created prior to imputation.

To protect against potential biases introduced by mortality selection in longitudinal studies of aging, results from parallel process models developed using the traditional assumption of data missing at random (MAR) were compared to estimates from parallel process growth models adjusted for the presence of non-random missing data (NMAR) on the outcomes of interest. Maximum likelihood estimation is the default estimator used by Mplus when estimating outcome trajectories, and this estimation assumes that missingness is not related to the underlying values of the outcome variables. In longitudinal studies where the outcome of interest is associated with the propensity for missing data, a NMAR mechanism is at work and may produce biased parameter estimates (Enders 2011). As cognitive and physical functioning have both been associated with increased risk of mortality (Lavery, Dodge, Snitz, and Ganguli 2009; Scott, Macera, Cornman, and Sharpe 1997; van Gelder et al. 2007), adjustment for mortality selection helps provide more accurate estimates of the underlying form of trajectories and the influence of covariates on these trajectories.

Under assumptions of NMAR, the data (Y, observed or unobserved) and probability of missingness (R represents if Y is observed or not) are jointly distributed (Enders 2010; Rubin 1976): $p\ (Yi, Ri \mid \theta, \phi)$. Here p represents the probability distribution, Yi is the outcome for case i, Ri is the missing data indicator for case i, θ are the growth model parameters that describe how Y is distributed, and ϕ includes parameters that describe the likelihood of missing data on Y. This differs from a MAR mechanism where the parameter used to indicate missingness (θ) is not estimated. The NMAR models used here, two forms of selection models, and a pattern mixture model, adjust Y for the outcome of missingness in different ways, but both essentially condition the estimation of the latent growth process on the propensity for missing data in that process.

Selection modeling produces the joint distribution of observed and missing data with a two part model: $p\ (Yi, Ri \mid \theta, \phi) = p\ (Yi \mid \theta)\ p\ (Ri \mid Yi, \phi)$. Here, $p\ (Yi \mid \theta)$ represents the marginal distribution of the growth model and $p\ (Ri \mid Yi, \phi)$ represents a conditional distribution produced by a regression model that uses Y to predict the probability of missing data (Enders 2010). Diggle-Kenward (DK) selection models and Wu-Carroll (WC) selection models are the two forms of selection models that will be used throughout this research.

For the DK selection model, logistic regression estimates are produced for each observation of data at each wave of measurement *t* by regressing the indicator of dropout on the observed values of the outcome variables at both *t* and *t* - 1. The logistic regression coefficient for dropout on current word-recall score at the given wave (β_t) and the coefficient for dropout on word-recall score at *t* - 1 (β_{t-1}) are estimated separately for each measurement of dropout and β_t and β_{t-1} are averaged across models to create global estimates for the coefficients β_1 and β_2. For ease of interpretation, the coefficients for β_1 and β_2 are re-parameterized to represent dependence on level and increment in the response variable ($\theta_1 = (\beta_1 + \beta_2)/2$ and $\theta_2 = (\beta_1 - \beta_2)/2$) (Diggle and Kenward 1994; Muthén, Asparouhov, Hunter, and Leuchter 2010). The missing data indicator is coded so logistic regression estimates represent the hazard probability of dropout, where 0 represents periods before dropout occurs, 1 represents the period where dropout occurs, and missing for times after dropout has occurred (Muthén and Masyn 2005; Muthén, Asparouhov, Hunter, and Leuchter 2010). The first measurement y_{i1} is observed for all individuals included in analysis and incomplete measurements thereafter are assumed to be caused by dropout only. Figure 2 presents the path diagram for a LGM adjusted by a DK selection model.

The WC selection model uses the individual growth trajectories to predict the probability of dropout at time *t* (Enders 2010). The outcome trajectory of interest is used to predict dropout at measurements taken from 2000 to 2008 (all individuals were observed at baseline measurement), allowing the probability of dropout to depend on both baseline word-recall and change in word-recall over the measurement period (including the unobserved scores from later assessments; Enders 2010). The coding of the dropout variable for the WC selection model is identical to the coding of the DK dropout indicator, and both utilize logistic regression equations to adjust the latent trajectories. Consistently significant paths between the dropout indicators and the intercept and slope of word-recall indicate the presence of nonrandom missing data. Figure 3 presents the path model of the un-conditional LGM adjusted by the WC selection model. Due to complexities in the parallel process modeling utilized in Chapter 5, models implementing WC selection modeling did not converge, thus WC selection models were only used in the more basic LGM analysis in Chapter 4.

In contrast to selection modeling, pattern mixture modeling changes the role of *Y* and *R* where the conditional distribution of *Y* represents the growth model parameters for only those cases that share the same missing data pattern, and *R* accounts for the number of missing data patterns ($p(Yi, Ri \mid \theta, \phi) = p\ (Yi \mid Ri\ , \theta)\ p\ (Ri \mid \phi)$). Figure 4 displays a diagram of the pattern mixture model. The pattern mixture model decomposes the average latent trajectory for each pattern of missing data and produces a weighted average trajectory based on the number of waves each individual was observed (the slope for the pattern mixture models was constrained to be equal for the 2nd and 3rd observations due to convergence issues). For example, the average intercept $\hat{\bar{\beta}}_0$ is determined by the number of missing data patterns (numeric superscript), the proportion of cases in missing data pattern p ($\hat{\pi}^{(p)}$), and the pattern-specific intercept estimate ($\hat{\beta}_0{}^{(p)}$), leading to the following equation representing three missing data patterns for simplicity:

$$\hat{\bar{\beta}}_0 = \hat{\pi}^{(1)}\hat{\beta}_0{}^{(1)} + \hat{\pi}^{(2)}\hat{\beta}_0{}^{(2)} + \hat{\pi}^{(3)}\hat{\beta}_0{}^{(3)}.$$

The coding of the dropout indicator for the pattern mixture model differs from the DK and WC selection models. The dropout indicator utilized in the pattern mixture model is a dummy variable representing the final period where dropout is observed. In contrast to the selection model coding where after an initial dropout, the individual is coded as missing for subsequent observations, the dropout dummy allows individuals to be re-observed after initial missingness, indicating dropout only at the last occurrence of dropout. With this coding scheme, the pattern mixture model is able to separate permanent dropout from intermittent missingness, and weight the trajectory for each subgroup accordingly.

As NMAR models include a set of un-testable assumptions about the nature of missing data (the MAR mechanism cannot be verified without the missing scores; Enders 2010), it is recommended that sensitivity analyses apply a number of NMAR methods to the same data, allowing examination of variation in the parameter estimates across models. Also, both the selection models and pattern mixture model include assumptions regarding model specification that can create biased estimates if not properly addressed. Specifically, both the DK and WC selection models rely on assumptions of multivariate normality, with the DK model making distributional assumptions about the repeated measures of the outcome variable, and the WC model assuming normally distributed individual intercepts and slopes (Enders 2010). While the pattern mixture model does not make distributional assumptions, it does rely on the user to explicitly specify parameters that are not estimable (those with fewer data points have fewer estimable parameters; Enders 2010). In the pattern mixture model, improperly specified parameter values can lead to improperly weighted trajectories, and result in biased estimates.

In this work, estimates from MAR and NMAR models were compared to understand how the varying assumptions used by the NMAR models influence the parameter estimates of interest, using results from traditional MAR LGMs as a reference point, as these methods are the most commonly used in studies employing LGMs. The traditional MAR model employs Full Information Maximum Likelihood to handle missing data, which basically utilizes all available data to estimate missing parameters for missing cases (Enders 2010). Full information maximum likelihood produces un-biased parameter estimates when missing data is MAR, but produces biased parameter estimates when data is NMAR. While the traditional model that assumes MAR data will be producing biased estimates of the trajectories of interest, most work utilizing LGMs would likely employ the FIML model, and is thus used as the reference model in all analyses.

Though sensitivity analyses are recommended for NMAR models, there are substantive considerations that may make a given NMAR model more applicable to a given research question (Enders 2010). For example, the DK selection model may be well suited to handle NMAR data caused by single realizations of the outcome measure, or short-term changes in the outcome measure, as the DK model adjusts the latent factors only by current observations of the outcome and the difference between the current outcome and the most recent prior observation. In contrast, the WC selection model may be better suited to handle NMAR data that results from changes in the complete trajectory of the outcome variable, as the WC model uses the entire outcome trajectory to adjust the latent factors. On the other hand, use of the pattern mixture approach to NMAR data provides its own set of benefits, namely that pattern mixture modeling stratifies the sample by missing data pattern rather than assuming that scores exist for the unobserved values, as do the forms of selection models discussed here. As each of these methods provides its own set of strengths and weaknesses, all following analyses use as many of the NMAR approaches as possible, comparing the results of these models to provide an understanding of how each model influences the measurement of socioeconomic variation in cognitive trajectories.

Example Results from NMAR models

To describe the extent of missing data in the analytic sample, and how LGMs with controls for NMAR data influence the measurement of the outcome trajectory in the presence of NMAR, a number of descriptive and predictive statistics are provided. First, patterns of dropout in the AHEAD sample are described. Using the observed average trajectory as a reference point, trajectory estimates produced by MAR and NMAR techniques are compared to better understand how each technique adjusts the outcome trajectory of interest. This is followed by discussion of the parameter estimates used to adjust for NMAR data in the DK and WC selection models, and pattern mixture models, concluding with examination of variation in covariate parameter estimates across models. This analysis documents the influence of NMAR data in the current study and provides an understanding of how each of the NMAR models produce adjusted estimates for the latent outcomes and observed predictor variables of interest. Observations were drawn from the AHEAD data, including individuals age 65 and over who were non-Hispanic white, black, or Hispanic, and who had non-missing values on the word-recall test in 1998. These restrictions produced a final sample size of N = 4,776.

Dropout and word-recall descriptive statistics. Table 3 provides the number of missing data patterns, the number of observations within each pattern, and the individual and cumulative percentages for each pattern. Thirty-one missing data patterns were found for the word-recall trajectory, with pattern 1 capturing individuals who were present at all 6 measurement periods, patterns 2 through 6 describing attrition assumed to be caused by mortality, and patterns 7 through 31 being the product of intermittent missingness. Around 93% of all missing values were captured by the six patterns describing mortality attrition, with the remaining 7% of missing data patterns being characterized as intermittent missingness. Interestingly, of those who did dropout due to mortality, dropout was observed more frequently earlier in the study, with decreasing numbers of individuals experiencing mortality later in the measurement interval.

Table 4 presents the observed mean trajectory of word-recall and the estimated mean trajectory produced by the MAR and NMAR models, and Figure

5 plots these estimates. The observed mean trajectory is composed of the observed average of word-recall at each time point, and is identical across models. The trajectories estimated by the MAR and NMAR models are produced from the estimated intercept and slope of word-recall in each model. As Figure 5 displays, the estimated mean trajectory and the trajectory estimated by the MAR model are nearly identical. Both the DK and WC selection models have an estimated intercept that is similar to the intercept of the MAR estimated trajectory, but both diverge from the slope estimated by the MAR model over time. Specifically, the WC estimated trajectory exhibits a slope with more rapid decline than that estimated by both the MAR and DK selection model, where the slope estimated by the DK selection model decreases slightly more rapidly than the MAR estimated trajectory. In contrast, the pattern mixture model has an estimated intercept that is greater than that estimated by the MAR and selection models, but a slope that is most similar to the slope estimated by the MAR model.

Results from NMAR models. Table 5 presents the logistic regression estimates produced by the WC and DK selection models, the regression estimates for the latent intercept and slope on dropout at each wave provided by the pattern mixture model, and the fit statistics for each model. Beginning with the fit statistics, the DK selection model provides the best model fit according to the loglikelihood, number of freely estimated parameters, and the Bayesian information criteria (BIC). The pattern mixture model exhibits a higher loglikelihood and BIC, likely due to the higher number of parameters in the model. Chi-square fit statistics are not provided for all models, restricting the use of formal statistical tests of model fit, thus the model fit statistics described should be interpreted with caution.

Turning to the parameter estimates for each model, all three NMAR models clearly indicated the presence of NMAR data. According to the WC selection model, those who dropout anytime throughout the observational period had significantly lower initial word-recall scores and significantly more rapid decline in word-recall over time than those who did not dropout. The DK model suggests that initial word-recall was significantly associated with dropout, where those with higher word-recall scores were less likely to dropout than those with lower initial word-recall scores. The DK estimate of change in word-recall on dropout provides evidence that initial word-recall scores were negatively associated with the likelihood of dropout, but the amount of change in word-recall from time $t - 1$ to time t was not significantly associated with dropout. The pattern mixture model provided supporting evidence for the presence of NMAR data, but from another perspective. Estimates from the pattern mixture model suggest that individuals who dropped out at any time point had significantly lower initial word-recall scores, with those dropping out earlier in the interval of observation having lower initial word-recall scores than those who dropped out later in the observation interval. Dropout was also negatively associated with slope, which itself was a negative value, meaning that those who dropped out had significantly more rapid decline in memory scores than those who did not drop out. Those who dropped out in the earliest observational periods had more rapid decline in word-recall scores than those who dropped out later, but there was not a clear trend in the relationship between observational period, dropout, and slope of word-recall as was observed for the intercept of word-recall.

Finally, comparing the estimates of covariates taken from the MAR and NMAR models provides insight into how each of the models influenced the parameter estimates for covariates of interest. Here, only basic covariates were included, namely age, gender (0 = male, 1 = female), race (non-Hispanic white, black, and Hispanic, with non-Hispanic white used as reference), and years of education. Table 6 presents estimates for these covariates across models, as well as the R-squared and covariance for the latent intercept and slope. Starting with the intercepts, the MAR and NMAR models provided consistent parameter estimates, in that all estimates were significant and in the same direction for each model. For age, the MAR and both selection models provided similar estimate values, where the age estimate from the pattern mixture model was smaller, which is substantiated by the fact that the 95% confidence intervals for the pattern mixture model age estimate did not overlap with the age estimate from the other models. The estimate for females was also smaller in the pattern mixture model, but confidence intervals did overlap with the estimates from the other models. For race/ethnicity, the models provided similar estimates, but the pattern mixture model produced a smaller estimate for blacks than other models. Finally, the estimate for education was again smaller in the pattern mixture model than in the other comparable models, but the confidence intervals for these estimates did overlap across all models. The R-squared for the MAR and the selection LGMs indicated that all models predicted a similar amount of variation in the latent intercept, but unfortunately, the pattern mixture model does not produce an R-squared value for interpretation.

For the estimates of covariates on the latent slope of word-recall, there was greater variation in the magnitude of estimates across models than was found for the intercept. Age was negatively associated with the slope in the DK and WC selection models, but this estimate was not significant in either the MAR or pattern mixture model. Females had significantly more rapid decline in word-recall score than men, with only the WC selection model providing evidence that gender was not significantly associated with word-recall slope. There was weak evidence that Hispanics had less rapid cognitive decline than whites, but this was not substantiated across models. Similarly, education displayed a weak negative relationship with word-recall slope across models. The WC selection model was able to predict a greater amount of variation in the slope than either the DK or MAR models, and the DK model predicted greater variation in the slope of word-recall than the MAR model. Finally, the covariance between the intercept and slope were strongest in the MAR and pattern mixture models and was weakest in the WC selection model.

Discussion

Using the AHEAD study as a source of information on the relationship between cognitive trajectories and lifecourse SES, this work provides a number of methodological advances to the study of cognition and aging. From a substantive perspective, the rich measurements of lifecourse SES available in the AHEAD study present an un-matched opportunity for examining how access to health-enabling resources across the lifecourse impacts change in cognitive health in the latest years of life. Methodologically, the AHEAD study represents a widely used dataset with issues of NMAR data that researchers commonly face. The AHEAD study provides a great opportunity to examine cognitive trajectories using sophisticated and novel methods designed to address the biases introduced by selective dropout. By comparing the results produced by the selection and pattern mixture models described above, this work contributes to the advancement of our understanding of socioeconomic predictors of cognitive change among the oldest old, and the methodological issues that beset all research examining longitudinal dynamics of health among the aging.

The example results of NMAR model section indicated the nature of dropout in the AHEAD sample being analyzed and how the MAR and NMAR LGMs influenced the measurement of cognitive trajectories, and how these models estimated the variation in cognitive trajectories associated with predictor variables. The majority of dropout present in the analytic sample can be characterized by dropout due to mortality or institutionalization, where dropout is an absorbing state without the possibility of follow-up. The parameter estimates of dropout taken from the DK and WC selection models, as well as the pattern mixture model, provided evidence that initial word-recall scores, and change in word-recall scores across time, were associated with the likelihood of dropout, and necessitate the use of methods that explicitly account for the presence of NMAR data.

The estimated intercept and slope of each model provided some evidence of how each model handles missing data. Both the DK and WC selection models had estimated intercepts comparable to the intercept estimated by the MAR model, but the selection models produced slope factors that exhibited more rapid decline over time than the slope estimated by the MAR model. The pattern mixture model seemed to place greater weight on observations that were observed continuously throughout the study, producing the largest intercept of all models and producing an estimated slope comparable to the MAR model. With these results, it seems reasonable that the selection models are better equipped to capture the nature of cognitive decline amongst individuals who selectively drop out of the study (i.e. those with low initial word-recall and more rapidly declining word-recall scores), where the pattern mixture model gives greater weight to the observations provided by those with advantageous cognitive profiles.

Comparing the estimated effect of covariates across models provided some evidence of the sensitivity of each method to predictors of cognitive change. Both of the selection models provided larger parameter estimates for age than either the MAR or pattern mixture model, and the selection models found significant age effects on the slope of cognitive decline where the MAR and pattern mixture model did not. The selection model estimates of word-recall intercept on black race/ethnicity, compared to non-Hispanic whites, were also of greater magnitude than estimates from the MAR and pattern mixture model. These results, supported by the differences in estimated trajectories between the selection models and the MAR and pattern mixture models, suggest that the selection models place greater weight on, and produce higher point estimates of, predictors of cognitive change for those who experience less favorable cognitive trajectories.

This chapter provides a strong starting point for more sophisticated analyses of cognitive trajectories using the AHEAD sample. The variation found in the estimated cognitive trajectories and the effects of covariates across models exemplifies the need for sensitivity analyses that compare the estimates provided by these models with differing assumptions and methods of addressing missing data. Compared to the traditional MAR LGM, the DK and WC selection models provide a set of tools better equipped to examine the experience of older adults who experience adverse cognitive trajectories, allowing the researcher to examine predictors of change for this select group of individuals. The pattern mixture model places greater emphasis on observations for those with advantageous cognitive profiles and provides estimates of socioeconomic and racial/ethnic variation that seem more conservative than those provided by the DK and WC selection models. By comparing the estimates produced across the LGM models discussed, a more nuanced understanding of cognitive change in socioeconomic context and the methods able to measure these outcomes is produced.

CHAPTER 4: VASCULAR AND COGNITIVE HEALTH IN SOCIAL CONTEXT

The number of Americans living to experience age-associated cognitive decline continues to increase, necessitating the identification of potentially malleable risk factors that can help alleviate the societal burden posed by cognitive aging. Decline in cognitive functioning increases the risk of developing functional impairments and disability (Fillenbaum et al. 1988; Park 1999; Reed, Jagust, and Seab 1989), in turn increasing risk of mortality (Gallacher et al. 2009; Shipley, Taylor, and Deary 2008; van Gelder et al. 2007). A number of cardiovascular risk factors and cardiovascular diseases are currently being examined as potential correlates of cognitive disease among the aging (Spiro and Brady 2008). To accurately estimate the influence of vascular health on cognitive health, acknowledging the differential prevalence and influence of vascular risk factors on health and mortality within socioeconomic and racial/ethnic sub-groups is essential, and to date, has been examined in only a limited number of studies.

To contribute to the literature examining the role of cardiovascular risk factors on cognitive aging, this project examined the relationship between memory trajectories (measured using a sum of immediate and delayed word-recall scores), diabetes, hypertension, heart problems, and stroke, with a clear focus on the socioeconomic and racial/ethnic context of aging. The Assets and Health Dynamics among the Oldest-Old (AHEAD) study provided a sample of non-institutionalized adults age 65 and over in 1998, with biennial follow-up continuing until 2008. Latent growth curve models with adjustment for non-random missing data caused by selective dropout were employed separately for white and black respondents, and multiplicative relations between indicators of cardiovascular health and lifecourse SES were examined. Results indicated that diabetes and heart problems increased the rate of memory decline in whites regardless of SES, where these risk factors were only associated with baseline word-recall for blacks when conditioned on gender and household assets. These results provide support for vascular hypotheses of cognitive aging, but more importantly attest to the significance of socioeconomic and racial/ethnic variation in vascular influences on cognitive health.

Method

Analyses employed the Assets and Health Dynamics among the Oldest Old Study (AHEAD) study. The initial AHEAD cohort measured in 1992 was born between 1890 and1923 and consisted of 11,965 individuals. Individual level weights were included, making the sample nearly representative of community-dwelling older adults in the United States in 1998. Restricting the analytic sample to white and black individuals who had non-missing word-recall scores at baseline measurement yielded a sample of 3,979 white and 555 black participants. Full description of the variables included in the following analyses is presented in Chapter 3.

Statistical analysis

Mplus version 6.1 (Muthén and Muthén 2010) was used to create and analyze multiple imputation data and estimate latent growth curve models conditional on non-random dropout. Specifications of the selection model prohibited the use of traditional SEM multiple group analyses. Complete direct effect models were analyzed for both white and black participants, followed by investigation of multiplicative effects between vascular health and lifecourse SES. Significant interaction terms were only present in the black sample, thus a final interaction model is only presented for blacks. Follow-up analyses were completed to investigate the nature of the significant interaction effects. Full description of latent growth models and NMAR data models is provided in Chapter 3.

Results

Descriptive statistics. Descriptive statistics are presented separately for white and black respondents in Table 1. Black respondents had a baseline total word-recall score more than 2 units lower than white respondents, though the magnitude of this difference dissipated over the 10-year measurement interval. The mean age at baseline measurement was between 79 – 80 years old, 65% of white participants were female, where 70% of black participants were female, and 53% of whites were married compared to only 32% of black participants. For measures of cardiovascular health, black individuals had a greater prevalence of doctor diagnosed hypertension and diabetes, while the prevalence of diagnosed heart problems was greater for white participants than for black participants. For both black and white respondents, 9% reported having had a stroke. Regarding indicators of lifecourse SES, blacks on average had lower household income and assets than whites, with white household assets being on average nearly four times greater than black household assets. Accordingly, black respondents on average had fewer years of education, fewer white-collar longest occupation job tenures, fewer parents with 8 or more years of education, less favorable childhood circumstances, and fewer fathers who worked in white-collar occupations.

NMAR model results. Table 7 presents the results from the NMAR adjustments incorporated into the latent growth models of word-recall, as well as the fit statistics for the traditional MAR latent growth model and each NMAR model. All estimates and fit statistics were taken from fully conditioned direct effect models. For the Wu-Carroll (WC) selection model, whites with lower word-recall scores in the second wave of measurement were more likely to drop out of the sample than those with higher word-recall scores, and whites with steeper trajectories of decline in word-recall scores were more likely to drop out than whites with less dramatic memory decline (white drop out intercept b = -0.32, $p < .001$; white drop out slope b = -.61, $p < .001$). For black individuals, word-recall score during the second interview was negatively associated with probability of dropout, though the individual latent slope was not significantly associated with the likelihood of dropout (black drop-out intercept b = -0.40, $p < .001$; black drop-out slope b = -.45, $p < .10$). The DK selection model provided results that support the conclusions of the WC selection model. In the DK model, word-recall at time t was predictive of dropout in subsequent waves for both whites and blacks, where the difference between word-recall scores from time t – 1 and time t was only predictive of dropout for white participants. Although using a different approach to capturing non-random dropout, the pattern mixture model also provided evidence that initial word-recall scores were significantly associated with dropout for both whites and blacks, where only whites were more likely to drop out given variation in their cognitive trajectories.

Concerning fit statistics, the combination of predictor variables included in the final direct effect models, regardless of missing data model, were better able to estimate the latent intercept and slope for blacks than for whites. Comparing the fit statistics of the three NMAR models, the pattern mixture models had the most optimal loglikelihood and BIC values for both whites and blacks. For whites, the WC model provided the worst model fit of all models, where for blacks, the DK selection model produced the worst fitting model. These results indicate that the dynamics of selective dropout likely vary by race/ethnicity, and different NMAR models may be better equipped to address the unique patterns of dropout presented by those of different racial/ethnic backgrounds.

Finally, Figure 6 and Figure 7 present the estimated word-recall trajectories for MAR and NMAR latent growth models for whites and blacks, respectively. For both the white and black samples, the MAR LGM and the DK LGM provide nearly identical estimates of the latent intercept and slope, although for blacks, the estimated slope diverges over time where the DK LGM has slightly higher estimated scores at the end of the measurement interval than the MAR LGM. For both samples, the pattern mixture LGM provided the highest estimated latent intercept of all models, and the WC LGM provided the lowest estimated latent intercept.

Multiple group latent growth results. Table 8 presents the results from the conditional latent growth analyses for the MAR and NMAR models of word-recall trajectories for whites, and Table 9 presents these results for black participants. Table 10 presents results from the MAR and NMAR LGMs exploring interactive effects found for black participants. To ease discussion across the MAR and NMAR models, only estimates that displayed statistically significant associations with word-recall trajectories across models will be presented, and when presenting specific estimates, results from traditional MAR models will be provided, unless otherwise noted.

In the final models containing the direct effect of covariates on latent growth curves of word-recall scores, the only indicator of cardiovascular health that predicted variation in baseline word-recall scores for whites was having been diagnosed as having a stroke, and for blacks, there were no significant associations between cardiovascular and cognitive health. For whites, having been diagnosed with stroke was associated with a lower predicted baseline word-recall score, and this association held significance across both the MAR and all NMAR models. Concerning change in word-recall scores over time, VDRFs were only significant predictors of cognitive change for whites. Reporting doctor diagnosed diabetes, heart problems, or stroke were each independently associated with cognitive decline in the white participants in the WC LGM, and being diagnosed with diabetes or stroke was associated with more rapid cognitive decline for whites in the DK model. These associations were not found in either the MAR model or the pattern mixture model. In the WC selection model, white individuals reporting a diabetes diagnosis had an average word-recall trajectory that declined .76 units greater than whites who did not report being diagnosed with diabetes (*b*

$= -.76$, $p < .001$). White participants reporting being diagnosed as having a stroke had word-recall scores that declined .64 units more rapidly than whites who had not been diagnosed with stroke, and diagnosis of heart problems was associated with a .42-unit decline over the ten year measurement interval when compared to whites who had not been diagnosed with heart problems ($b = -.42$, $p < .01$).

Regarding covariates that influenced cognitive trajectories similarly for whites and blacks across the MAR and NMAR models, age, education, and longest-tenured occupation were significant predictors of baseline word-recall scores for all participants. Specifically, age was negatively associated with initial word-recall score (white $b = -.22$, $p < .001$; black $b = -.17$, $p < .001$) and years of education (white $b = .17$, $p < .001$; black $b = .24$, $p < .001$) were positively associated with initial word-recall score, where reporting longest occupation tenure in blue-collar occupations (white $b = -.57$, $p < .001$; black $b = -.96$, $p < .05$) or as a homemaker (white $b = -.69$, $p < .001$; black $b = -1.65$, $p < .01$) predicted significantly lower baseline word-recall scores than those reporting longest tenure in white-collar occupations. Females had consistently higher predicted baseline word-recall than their male counterparts, although this relationship was only approaching significance for blacks in the pattern mixture model (white $b = 1.11$, $p < .001$; black $b = .83$, $p < .01$; pattern mixture model black $b = .47$, $p = .09$). None of the covariates predicted significant variation in word-recall scores over time consistently for white and black respondents.

Covariates that were consistently associated with word-recall trajectories for whites but not for blacks included marital status, household assets, and mother's education. Marital status was negatively associated with initial word-recall scores for whites (white $b = -.42$, $p < .001$; black $b = -.40$, $p = .22$). Household assets were positively associated with baseline word-recall for whites, where a ten-percent increase in log-transformed household assets corresponded to a .01 unit increase in baseline word-recall score (white $b = .10$, $p < .001$; black $b = .02$, $p = .41$; .10/10 = .01). Reporting that the respondent's mother had attained 8 or more years of education predicted a .35-unit increase in white baseline word-recall (white $b = .35$, $p < .01$; black $b = -.22$, $p = .51$). For black participants, reporting longest tenure in occupations other than those defined as white-collar, blue-collar, or homemaker corresponded to lower initial word-recall scores than those in white-collar occupations, although this effect was not significant in the pattern mixture model (white $b = -.15$, $p = .32$; black $b = -1.09$, $p < .05$; pattern mixture black $b = -.79$, $p = .11$).

Significant predictors of the latent slope that differed for white and black participants included age, gender, education, and longest tenure as a homemaker, although none of these estimates were significant across MAR and NMAR models. Due to inconsistencies across the LGMs, the direction and magnitude of these effects will not be interpreted.

Investigating multiplicative effects. Interactions were explored within indicators of cardiovascular health, between indicators of cardiovascular health and gender, and between each indicator of cardiovascular health and lifetime SES. All interactions were created prior to imputation, all continuous variables were mean-centered, and the interactive term was a product of multiplying the two direct effects of interest. There were no significant interactions found between cardiovascular health, gender, and lifecourse SES for whites, but significant interactive effects emerged for blacks, specifically between reporting doctor diagnosed diabetes, household assets, and longest occupation tenure in blue-collar positions. Table 10 presents these results.

In the final interaction model for blacks, an interaction between doctor diagnosed diabetes and household assets emerged on baseline word-recall (b = -.17, $p < .01$). Figure 8 and Figure 9 present the nature of this relationship (using estimates from the traditional LGM model), displaying that household assets were differentially associated with baseline word-recall scores for black non-diabetics/diabetics, where for non-diabetics, increasing household assets were positively associated with initial word-recall score, and for black diabetics, household assets were negatively associated with initial word-recall score. Figure 9 displays that the greatest difference in initial word-recall score for black diabetics and non-diabetics existed at the lowest range of household assets, with the difference dissipating as household assets increased.

Figure 10 displays the significant interaction found between the latent slope of word-recall, blue-collar occupation tenure, and diabetes diagnosis (also, the latent intercept of this interaction was approaching statistical significance; intercept b = -1.25, p = .05; slope b = 2.96, $p < .05$). Blacks reporting doctor diagnosed diabetes and blue-collar occupational tenure had lower initial word-recall scores than black diabetics reporting white-collar occupational tenures, although this difference was only approaching statistical significance. Black individuals with diabetes reporting longest occupational tenure in blue-collar jobs had significantly less rapid decline in word-recall scores than black diabetics reporting longest occupational tenure in white-collar positions.

Discussion

This study examined the strength of the vascular hypothesis of cognitive decline in the socioeconomic and racial/ethnic context where individuals and their health develop inequitably. For white Americans, evidence for the influence of vascular health on memory trajectories was found for diabetes and heart problems, though there was substantial variation in the strength and significance of these estimates across MAR and NMAR models. For black Americans, diabetes was differentially associated with word-recall trajectories based on household assets and occupation. In addition to indicators of vascular health, SES developed across the lifecourse influenced cognition, especially baseline scores, with both consistencies and points of divergence between whites and blacks. The modeling strategy provided some evidence of the efficacy of how well the set of explanatory variables were able to predict variation in memory decline and provides insight into the relationship between cognition and selective dropout in longitudinal studies of cognitive health.

The most important findings of this study showed that VDFRs were differentially associated with memory for white and black respondents. While there was some evidence that heart problems and diabetes influenced more rapid cognitive decline in aging whites directly, diabetes was not significantly associated with memory for blacks until the relationship between diabetes, household assets, and occupation were accounted for. Household assets, representing the monetary and materiel resources accumulated across a lifetime, were associated with the influence of doctor diagnosed diabetes on baseline word-recall for blacks, but the influence of assets did not predict substantial variation in trajectories of memory for diabetic and non-diabetic blacks. Also, black diabetics reporting longest occupational tenure in blue-collar occupations had baseline memory that was lower than black white-collar diabetics (although not statistically significant), though black white-collar diabetics had significantly more rapid memory decline than both black blue-collar diabetics and all blacks that were non-diabetic. These findings assert that the study of vascular hypotheses of cognitive aging must take into account the racial/ethnic and socioeconomic characteristics of study participants before examining the relationship between vascular and cognitive health, as the association between VDRFs and memory for black participants were only made apparent when these relationships were conditional on SES.

The observed relationships between diabetes, household assets, and occupation indicate complex mechanisms through which SES can influence the relationship between vascular and cognitive health for black Americans. To compound the complexity of this issue, mortality selection and survivorship is a likely cause for the observed relationships between diabetes, SES, and memory trajectories. As SES is strongly associated with diabetes in blacks (Link and McKinlay 2009) and black diabetics experience relatively high mortality (Kuchibhatla and Fillenbaum 2002), the observed associations between diabetes, SES, and cognition may be a result of the mortality selection. Using information from a recent National Vital Statistics report, the possible influence of mortality selection on the observed results become clearer. For whites born between 1929-1931, life expectancy was around 61 years at birth, as compared to about 49 years for blacks (Arias 2010). Between 1999-2001, life expectancy for whites age 70 was 14 years, compared to blacks who had a predicted 13 years of life ahead (Arias 2010). These figures indicate that Blacks who survive to the age of 70, around the average age of participants at baseline, are relatively rare when compared to whites. Furthermore, blacks aged 70 years old in 1999-2001 had a remaining number of life-years similar to whites. Blacks who survive to the ages of participants being analyzed here are healthier than blacks that do not survive to these ages, and these factors are likely influencing the associations observed here. Socioeconomic status and VDRFs are also both predictive of mortality, in turn producing a number of mechanisms that influence the survivorship of the individuals being analyzed. The concept of selective survivorship is helpful when attempting to understand the significant interactions found between diabetes and SES that predicted variation in black memory trajectories.

The measure of accumulated assets used here captures access to health-enabling monetary holdings across the lifecourse, and likely influences the development of lifestyle choices that can predispose one towards developing diabetes. Assets were positively associated with baseline memory for black non-diabetics, meaning that black individuals who have survived to advanced old age without developing diabetes may also be experiencing protective effects of monetary resources on cognition and memory. For black diabetics, increased household assets may be contributing to the ability to survive into later stages of old age, making blacks with greater assets and diabetes better able to withstand the negative impact of diabetes on survivorship, although diabetes appears to be still contributing to lower initial memory in this group.

For blacks, longest occupation tenure exhibited significant interactions with diabetes diagnosis, in turn predicting memory change over time. Longest occupational tenure indicates the working environment where the individual spent the greatest amount of their working life, and subsequently had the greatest exposure to the prestige, occupational hazards, and tasks associated with that position. Black individuals reporting longest occupational tenure in white-collar settings are a relatively select group, and regardless of their diabetes status, these blacks had higher initial memory than blacks that spent their working lives in blue-collar occupations. When compared to non-diabetics with similar occupational tenure, and all blacks reporting blue-collar occupations, black white-collar diabetics experienced dramatic decline in their memory scores. For blacks in white-collar occupations, it appears that diabetes has a significantly negative influence on change in memory over time. Compared to blacks in blue-collar occupations that have survived to the late ages being analyzed here, white-collar blacks, as a whole, may be more susceptible to the negative influence of diabetes on memory.

Other explanations for the associations found between diabetes, lifecourse SES, and memory for blacks include under diagnosis of diabetes in the black sample with lower lifecourse SES, as well as floor effects that make blacks with lower initial memory scores less susceptible to decline in memory over time. Between 1999-2002, 7.6% of black and 6.9% of black women age 65 or older had undiagnosed diabetes (Cowie et al. 2006). Coupled with household assets, some of the observed differences in baseline memory found for blacks in relation to diabetes, especially at the lowest range of assets (see Figure 9), could be a result of undiagnosed diabetes. In relation to the dramatic decline observed in memory trajectory for black white-collar diabetics, the predicted slope of decline may be artificially sharper relative to the other groups displayed in Figure 10 due to the fact that these individuals had the highest baseline memory of all subgroups being compared. Since black white collar-diabetics had a greater amount of baseline memory that could decline over time as compared to black white-collar non-diabetics and blacks with blue-collar occupational tenure, the predicted slope was less susceptible to floor effects than the comparison groups, giving the appearance that predicted memory at the end of the measurement interval was substantially lower for black white-collar diabetics. Initial investigation of quadratic effects on the analytic samples of whites and blacks were not significant, but may have provided a more accurate estimate of the predicted trajectory for this subgroup.

Though VDRFs proved to be significantly associated with memory trajectories, measures of lifecourse SES continued to exhibit significant relationships with memory in light of controls for vascular health. Education and longest tenure in white-collar occupations were predictive of higher initial word-recall scores in both white and black participants, and household assets, mother's education, and father's occupation were each directly associated with baseline memory in whites but not blacks. The set of socioeconomic indicators included in this analysis exhibited much more consistent relationships with baseline word-recall than change in word-recall over time, meaning that variation in memory and SES develop in tandem over an individual's lifetime, with these differences persisting throughout the course of aging. This finding suggests that those seeking to alleviate cognitive disparities in aging must focus upstream, in terms of both the structural determinants of inequitable access to health-enabling resources, as well as by intervening at earlier points in the lifecourse when an individual's potential for cognitive development are more malleable.

Finally, measures of model fit indicated that the modeling strategy and set of predictor variables employed were better able to capture variation in black as compared to white memory trajectories. As white participants started with higher initial memory scores than blacks yet experienced more rapid decline in word-recall, there is likely greater variation in white memory trajectories to be predicted than for black individuals. In addition, the trajectory of word-recall for whites was more consistently associated with likelihood of attrition compared to blacks. Thus, processes of mortality selection may be more diverse in the white population that reaches middle-to-late old age. Inversely, black individuals who reach these ages may be more select, thus exhibiting greater homogeneity in trajectories of memory, SES, and mortality.

Limitations. A number of potential limitations restrict the accuracy of this study, although multiple steps were taken to reduce the potential biases introduced by the unique dynamics of cognitive aging. Exclusion of controls for test-retest effects was necessitated by the models used to control for mortality selection. Without accounting for the practice effects that occur over repeated exposure to cognitive tests (Glymour, Weuve, and Chen 2008), trajectories of memory may be artificially biased upwards as participants use the knowledge developed through exposure to previous tests to inform their preparation for, and execution of, future tests. A central aim of this research was to compare a number of MAR and NMAR methods of modeling longitudinal data, and the inclusion of a simple indicator of being exposed to the word-recall test more than once created problems in the convergence of the NMAR models, thus the choice was made to exclude controls for practice effects. Hence, the observed estimates may be artificially biased upwards due to the uncontrolled influence of practice effects.

Another potential source of bias in the estimate of cognitive trajectories was the unrestricted use of assistive devices that could bias the estimates of memory upwards. As the AHEAD study is conducted over the telephone, there was no control over the use of assistive devices such as paper and pencil that would restrict the accurate measurement of working memory. While providing the ability to test a large sample of older adults across the United States in a cost-effective manner, the use of telephone surveys to conduct cognitive assessments introduces potential biases into the measures being analyzed here.

While practice effects and the measurement of word-recall scores over the telephone pose threats to the accuracy of the estimates of the relationship between VDRFs, lifecourse SES, and trajectories of memory developed here, the use of sensitivity analysis to compare the results of statistical methods designed to control for potential biases introduced by non-random missing data provides the findings of this analysis confidence against biases introduced by mortality selection.

CHAPTER 5: SOCIOECONOMIC VARIATION IN THE CO-EVOLUTION OF COGNITIVE DECLINE AND FUNCTIONAL LIMITATIONS

For developed countries, increasing numbers of adults are living to the furthest bounds of human longevity. The population health costs of morbidities common to late old age will inevitably place a growing burden on healthcare and social support systems that provide care for the aging. Two of the most costly health problems associated with aging are cognitive decline and increasing functional limitations, and these morbidities are often dealt in pairs. A substantial amount of research has shown declines in cognitive abilities increase the risk of functional limitations (McGuire, Ford, and Ajani 2005; Moody-Ayers et al. 2005; Stuck et al. 1999), and both in turn increase the risk of disability and mortality (Gallacher et al. 2009; Scott et al. 1997). Evidence suggests that functional limitations and disability influence cognitive outcomes, with both cognitive and functional health mutually influencing the development of one another (Atkinson et al. 2005; Black and Rush 2002). Studies of socioeconomic variation in trajectories of mind/body health among the aged are present, but work that focuses on the socioeconomic context where cognitive and functional health co-evolve are less apparent. Another issue hampering examinations of the dynamics of co-morbidity development is mortality selection, creating potentially biased estimates in studies that do not adjust for presence of non-random missing data. Understanding the inter-relation between cognitive and functional health outcomes is essential for those responsible with the planning of health policy that will serve to protect from the manifold costs of an aging population.

To identify the complex relationship between cognitive decline, functional limitations, and socioeconomic resources, this project utilized parallel process latent growth modeling with adjustment for mortality selection to model the co-evolution of cognitive abilities (as measured by immediate and delayed word-recall scores) and functional limitations over a ten-year period. Observations were drawn from the Assets and Health Dynamics among the Oldest Old Study (AHEAD; 1998-2008). After determining the measurement model that best captures the inter-relation between development of cognitive and functional limitations, measurements of socioeconomic status (SES) were introduced to understand how differential access to health-enabling resources contributes to variation in the relationship between trajectories of cognitive and functional health among America's oldest old. The measures of SES included account for access to socioeconomic resources across the lifecourse, including indicators of educational and monetary resources at time of interview, occupational position across working life, and finally, retrospective indicators of childhood socioeconomic circumstances. Estimates produced from traditional approaches to latent growth modeling in the presence of missing data were compared to estimates taken from Diggle-Kenward (DK) selection models and pattern mixture models, designed to control for the presence of non-random missing data on both growth trajectories being analyzed. By focusing on the inter-related development of cognitive and functional limitations controlling for a robust set of indicators of

SES across the lifecourse, and by using innovative methods to account for the presence of mortality selection, this work provides a unique contribution to the study of health inequalities amongst aging Americans.

Method

Created as a national panel survey employing biennial assessment of America's aging population, the Health and Retirement Study (HRS) began as a representative sample of the U.S. population between ages 51-61 in 1992 (including spouses regardless of age; Hauser and Weir 2010). To supplement the HRS, the study of the Asset and Health Dynamics among the Oldest Old (AHEAD) began in 1993 as a spinoff of the HRS that focuses on Americans considered to be the oldest-old; birth cohorts born in 1923 or earlier, or who were 70 years of age or older in 1993 (Juster and Suzman 1995). This research utilizes the AHEAD survey from 1998 to 2008. Measurements of cognitive performance and functional limitations used in this analysis were taken over a decade ranging from 1998 to 2008, with all predictor variables being measured in 1998. Individual level weights were utilized, making the sample nearly representative of community-dwelling older adults in the United States in 1998. Restricting the analytic sample to individuals who had non-missing word-recall scores and function limitation counts in 1998, were age 65 or over at baseline measurement, and excluding individuals who were of a race/ethnicity other than white, black, or Hispanic resulted in a final sample size of N = 4,653. Full description of the variables included in following analyses is presented in Chapter 3.

Statistical analysis. Mplus version 6.1 (Muthén and Muthén 2010) was used to create and analyze multiple imputation data and estimate parallel process latent growth models. Latent growth modeling (LGM) is considered an extension of structural equation modeling (SEM) where the individual parameters that create trajectories are treated as latent variables (Bollen and Curran 2006). Parallel process latent growth modeling is an extension of LGM where an intercept and slope are estimated for two or more concurrent outcome variables of interest (Muthén and Curran 1997). To take advantage of the temporal ordering of the latent intercept and slope for each process, the structural paths investigated in this project extended from the intercept of one construct to the latent slope of the other construct. This specification assured that both latent and observed predictor variables preceded the specific outcomes of interest, namely change in cognition and functional limitations over time. An un-specified model that allowed all latent variables to correlate (excluding correlations between the latent intercept and slope across processes) was used as a baseline model, which served as a point of comparison for models that imposed theoretically relevant structural paths on the model. The four structural models examined are displayed in Figure 11. Importantly, the latent intercept for cognitive and functional trajectories were allowed to correlate in all models, assuring that the variation in intercepts used to predict change in the slope of the alternate process had been adjusted for the correlation between cognitive and functional health at baseline. To examine the possible moderating effects of lifecourse SES in the relation between baseline cognitive and functional health and change in the alternate process, change in each process was regressed on interactions specified between each indicator of SES and the latent intercept of the alternate process. Figure 12 presents the final structural model, conditioned by covariates, with interactions on the latent slope of each process specified between the observed variables and the latent intercept of each process.

Missing data. Mplus provides a useful suite of tools to account for multiple forms of missing data. Multiple imputation was used to account for missing data in predictor variables (20 datasets were imputed and analyzed, two variables had greater than 10% missing data; father's education > = 8 years = 10.12% missing; father white-collar occupation = 13.54%). All descriptive statistics reflect averages across the 20 imputed datasets.

To adjust for NMAR data on the cognitive and functional trajectories being analyzed, a Diggle-Kenward selection model and a pattern mixture model were utilized. These methods are described thoroughly in Chapter 3, and Figure 13 presents a diagram of an un-adjusted parallel-process model, Figure 14 provides a diagram of a parallel-process model adjusted by a Diggle-Kenward selection model, and Figure 15 presents the parallel-process model adjusted by a pattern mixture model. Missing data patterns in the trajectories of word-recall and functional limitations were analyzed separately, providing unique dropout indictors that were subsequently used to adjust the trajectory of the given health outcome based on its own missing data pattern. These differing approaches to controlling for NMAR data incorporate un-testable assumptions, requiring a sensitivity analysis to observe variation in estimates across models. To facilitate this process, Tables 13, 14, and 15 compare results from each of the NMAR models described to estimates taken from a traditional latent growth model. Table 11 presents the logistic regression estimates produced by the DK selection model, as well as the regression estimates of the latent intercept and slope on dropout at each wave provided by the pattern mixture model.

Results

Table 2 provides descriptive statistics for measures of word-recall, functional limitations, and sociodemographics, as well as percentages of observed dropout for both word-recall and functional limitations. The average number of words recalled at baseline on the immediate and delayed word-recall score tasks was 8.5, and this declined over the decade of observation to 5.7 words, or a 32.19% decrease. The average participant had around 3 functional limitations at baseline, which increased to about 6 functional limitations by 2008, or about an 89% increase. Dropout trends are reported for word-recall and functional limitations separately as dropout patterns were different across processes. For word-recall, around 67% of all participants had dropped out of the sample by the final observation, where about 63% of those reporting functional limitations had dropped out of the sample by 2008.

For observed predictor variables, the mean age at baseline was 79 years old, the racial/ethnic composition of the initial sample was 90% white, 6% black, and 4% Hispanic, 66% of the initial sample was female, and about 50% were married. For measures of adult SES, around 42% of respondents reported longest occupational tenure in white-collar positions, 30% in blue-collar occupations, 9%

as home-makers, and 19% in other employment settings/situations, and about equal proportions reported attaining less than, equal to, or greater than a high school degree. The average household income was around $31,000 and the average household assets were worth $280,000. For measures of childhood SES, 59% reported that their mothers had attained 8 or more years of education, 55% reported their father had 8 or more years of education, and about 24% reported that their father worked in a white-collar occupation.

Estimates from NMAR data models. Table 11 presents the estimates from the DK selection model and the pattern mixture model adjustments to the final structural model. The estimates provided in Table 11 were taken from the final structural model conditioned on all covariates. Both the DK selection model and pattern mixture model suggest that dropout was non-random in both trajectories of interest. Focusing on the re-parameterized estimates from the DK selection model, both the initial level of word-recall and the increment between word-recall scores from $t - 1$ and t were negatively associated with the hazard of dropout. Conversely, initial functional limitations and change in functional limitations from $t - 1$ to t were positively associated with the hazard of dropout. Put simply, those with low initial word-recall scores and who displayed rapid decline across time in word-recall scores were more likely to dropout, and those with greater initial functional limitation and greater increases were more likely to dropout.

Findings from the pattern mixture model also support the necessity of controlling for data NMAR in this study. For word-recall, those who dropped out in the earliest phases of the study had lower initial word-recall scores than those dropping out in the later phases of the study, to the point that dropout in 2008 was not significantly associated with initial word-recall score. For change in word-recall, the effects of dropout for observations at 2000 and 2002 were constrained to be equal due to convergence issues, but those who dropped out of the study between 2004 and 2008 had significantly more rapid cognitive decline than those who did not drop out. The pattern mixture model estimates of functional limitations show that those with greater initial functional limitations were more likely to drop out early in the study, and the strength of association between initial functional limitations and dropout decreased over time. Those who dropped out in 2004 experienced significantly greater increases in slope over time than those who had not dropped out, but this association weakened for following observations.

Estimates from both the DK model and the pattern mixture model suggest that those who were initially healthier and who experienced less rapid change towards poor health had a greater likelihood of being observed throughout the study, thus introducing potential biases into estimates that did not control for these dynamics.

Parallel-process structural model. Table 12 presents the model fit statistics for the four structural models pictured in Figure 11. Model fit statistics are provided separately for the latent growth model with assumptions of data MAR, the DK selection model, and the pattern mixture model. Model 1 represents the parallel-process model with no causal structure, Model 2 adds to Model 1 a regression path from initial word-recall score to the slope of functional limitations, Model 3 adds to Model 1 a regression path from initial functional limitations to the slope of word-recall score, and Model 4 adds to Model 1 both paths represented in Model 2 and Model 3. Traditional chi-square goodness of fit tests are not possible with the current model specifications, thus requiring an informal comparison of available fit statistics to determine the most appropriate structural model. For all fit statistics including the log-likelihood, Akaike information criteria (AIC), Bayseian information criteria (BIC), and sample-adjusted BIC, Model 4 seems to fit the data better than less restricted models, and this is consistent for both MAR and DK selection models. The pattern mixture model provides some conflicting evidence about the best fitting model, with the log-likelihood and AIC suggesting Model 4 provides the best fit to the data, with both versions of the BIC suggesting Model 3 provides the best model fit. With the majority of evidence suggesting that model 4 provides the best model fit of all hypothesized structural models, Model 4 was used in the subsequent analyses.

Predictors of word-recall and functional limitation trajectories. Tables 13, 14, and 15 present the estimates of latent and observed predictor variables on trajectories of word-recall and functional limitations for parallel-process models with MAR assumptions, the DK selection model, and pattern mixture model, respectively. To aid interpretation of these estimates across models with differing assumptions, discussion of the latent trajectories and relationships between these variables will be discussed first, followed by comparison of estimates for covariates that displayed similarities and differences across models.

Beginning with the estimates of the latent intercept and slope for trajectories of word-recall and functional limitations, there was substantial variation in the estimated latent intercept and slope across models. In the parallel-process model assuming MAR data, the estimated word-recall intercept was 8.13 with an estimated slope of -2.93, where functional limitations had an estimated intercept of 2.41 and an estimated slope of 3.70. The DK model produced estimated intercepts for both word-recall and functional limitations similar to those produced by the MAR model, but produced estimated slopes indicating more dramatic change towards poor health in both processes. In contrast, the pattern mixture model produced estimates of the latent intercept that were more advantageous than the MAR model (higher initial word-recall scores and lower initial functional limitations), but produced estimates of the latent slope that were similar to those produced by the MAR parallel-process model. The varying estimated values for the trajectories of word-recall and functional limitations signify the differential adjustments to the outcome trajectories provided by the DK and pattern mixture models.

Examining the estimates of the latent predictor variables on the slope of word-recall and functional limitations reveals consistent effects of initial word-recall on change in functional limitations across models with different missing data assumptions, but this was not true for the effect of initial number of functional limitations on word-recall. Specifically, initial word-recall scores were consistently negatively associated with change in functional limitations, with the MAR model providing the smallest effect ($b = -.08$, $p < .05$), followed by the pattern mixture model ($b = -.13$, $p < .001$), and finally, the DK model ($b = -.22$, $p < .001$). For the effect of initial functional limitations on change in word-recall scores, the model with MAR assumption displayed a significant positive effect of initial functional limitations on word-recall trajectory ($b = .09$, $p < .05$), which is in contrast to the significant association between these variables found in the DK model ($b = -.18$, $p < .001$). This estimate was not significant in the pattern mixture model, and may explain the better-model fit of Model 3 according to the pattern mixture fit statistics displayed in Table 12.

Turning to the estimates of observed predictor variables on the latent trajectories of word-recall and functional limitations, the majority of estimates that were significant predictors of the latent intercept for both word-recall and functional limitations were significant and in the same direction across models. For baseline word-recall, older individuals had lower scores than younger individuals, blacks and Hispanics had lower scores than whites, females had higher scores than males, and those who were married had lower scores than those who were un-married. Compared to those reporting longest occupational tenure in white-collar positions, those reporting blue-collar occupational tenure or longest occupational tenure as a homemaker had lower initial word-recall scores. Education was positively associated with baseline word-recall, as were household income and assets. Finally, those reporting that their mother had 8 or more years of education had higher initial word-recall scores than those whose mothers had less than 8 years of education, and those who reported that their father had a white-collar occupation had better initial word-recall than those whose fathers were employed in non-white-collar settings.

Fewer predictor variables were significantly associated with baseline functional limitation. Being older and being female were associated with more initial functional limitations, and Hispanics had significantly fewer initial functional limitations than whites. Those reporting occupational tenure in positions other than white-collar, blue-collar, or homemaker had more initial functional limitations than those with white-collar occupational tenure, and those with less than a high school degree had more initial functional limitations than those with a high school degree. Both household assets and household income were protective against initial functional limitations, though the effect of household income was not significant across models with differing assumptions about missing data on the trajectory of functional limitations.

Concerning the estimated slopes of word-recall, far fewer predictor variables were significantly associated with change over time than initial status, and there were more inconsistencies across MAR and NMAR models. For slope of word-recall, those reporting occupational tenure in blue-collar positions had significantly less rapid cognitive decline than those in white-collar positions, which may be a result of their initially lower starting values. Age was inconsistently associated with word-recall trajectory, being significantly associated with more rapid cognitive decline only in the DK selection model. According to the MAR and pattern mixture models, females had significantly more rapid decline in word-recall than males, but this was not confirmed in the DK model.

For slope of functional limitations, age was the only significant predictor across models, displaying a positive association with increase in functional limitations. Both Hispanics and females had less rapid increase in functional limitations than their reference categories, but these effects were only significant in the DK model. There was some evidence that those who were married had less rapid increase in functional limitations, but this was only confirmed in the MAR and pattern mixture model. Finally, household assets were positively associated with increasing functional limitations in the MAR and pattern mixture model, but this association was non-significant in the DK model.

Interactive effects between latent and observed variables. Table 16 presents the significant interaction effects found between latent intercepts, lifecourse SES, and trajectories of cognitive and functional health for the MAR parallel-process model. Interactions were explored separately for MAR and NMAR assumptions, and only interactive effects that were significant in all models were probed further. Furthermore, parallel-process model specifications restricted the types of probing that could be conducted, allowing only for post-hoc tests of differences between groups in the point estimate of interest. Two significant interactions were found between latent intercepts and indicators of SES; functional limitations slope on the interaction between initial word-recall and female, and word-recall slope on the interaction between initial functional limitations and household income.

Estimating the influence of initial word-recall on change in functional limitations separately for men and women, controlling only for age , revealed evidence that initial word-recall had a statistically significant relationship with change in functional limitations in men, but this relationship was not significant for women (male $b = -.14$, $SE = .06$, $p < .05$; female $b = -.03$, $SE = .04$, $p = .45$). Greater values in initial word-recall may protect men from increase in functional limitations more than women, however, this difference cannot be considered statistically significant as the 95% confidence intervals for the point estimate had considerable overlap (shown in Figure 16).

To probe the interaction between household income and initial functional limitations, the effect of initial functional limitations on word-recall slope was assessed separately for participants one standard deviation above the mean of household income and one standard deviation below the mean of household income, including controls for age (shown in Figure 17). For the group with household income one standard deviation above the mean, initial functional limitations did not significantly predict change in word-recall ($b = -.16$, $SE = .12$, $p = .17$). For participants one standard deviation below the mean of household income, initial functional limitations were positively associated with the slope of word-recall, where a one unit increase in initial functional limitations predicted a .29 unit increase in the slope of word-recall ($b = .29$, $SE = .09$, $p < .01$). Furthermore, because the 95% confidence intervals do not overlap between these comparison groups, evidence suggests that there was a significant difference in the effect of initial functional limitations on word-recall score for those with different amounts of household income (> = 1 SD HH Inc. 95% CI = -.39 to .07, < = - 1 SD HH Inc. 95% CI = .10 to .48).

Discussion

This research examined the co-evolution of cognitive and functional health in the context of lifecourse SES, using methods able to address the potential biases introduced into longitudinal studies of aging through mortality selection. Greater initial memory scores were consistently associated with less rapid increase in functional limitations, with conflicting evidence regarding the direction and amount of variation in cognitive trajectories that could be attributed to initial functional limitations. Variation in the influence of initial cognitive and functional health on change in the opposite process was found for gender and household income, indicating the importance of sociodemographic mechanisms in the co-evolution of mind/body health. Multiple indicators of lifecourse SES were found to predict variation in initial memory scores and functional limitations, but fewer measures of lifecourse SES were associated with change in these outcomes over time. After discussing the structural relationship between cognitive and functional health trajectories, and the role of lifecourse SES in their co-development, a brief discussion of the contributions and limitations of the modeling strategy employed is provided.

Through modeling the development of cognitive and functional health as contingent processes, findings support the conclusion that initial word-recall is a consistent and significant predictor of change in functional limitations. Across all treatments of missing data, those with better working memory had less rapid increase in functional limitations, and this was accounting for initial functional limitations, the association between change in cognitive and functional health across time, and socioeconomic variation in both trajectories. Initial functional limitations displayed an inconsistent relationship with change in word-recall, with estimates from the traditional MAR model showing protective effects, and estimates from the pattern mixture model displaying significant influence towards more rapidly declining cognitive function. As initial word-recall was shown to consistently protect individuals from increasing functional limitations, this work supports others finding that cognitive function is a predecessor to functional decline, and can be targeted by professional as an early warning sign of potential functional health problems in the future. The casual mechanism driving this association is somewhat unclear, with initial memory influencing the manifestation of functional limitations over time, possibly through the individual's perceived decrease in cognitive function driving reduced physical activity and self-care that could lead to increased functional limitations, or possibly reduced memory being perceived by the individual's social support system who in turn actively constrains the opportunities for physical functioning and conditioning. Controlling for the relation between cognitive and physical change over time reduces the likelihood that senescence in both processes was driving these results, and provides further support for the conclusion that current memory can be associated with future functional limitations for older adults.

In the final model examining interactive effects between observed and latent predictor variables, there was some evidence that initial word-recall was especially protective of future functional limitations for men. While significant differences were not found in this effect when comparing the point estimates of men and women, men did seem to experience greater benefit from higher initial memory scores than women. All estimates were controlled for age, decreasing the likelihood that gender differences in longevity were contributing to the observed estimates, but it is also likely that men who had survived to the relatively late age of the participants included in analyses may be select in terms of being in good health. Men included in the sample may have had higher initial word-recall scores, and were also predisposed to have more favorable functional trajectories, meaning the observed finding may be an artifact of mortality selection occurring prior to observation. Alternatively, men's functional health may be more sensitive to change in other dimensions of health as compared to women since at comparable ages, men's overall health may be more fragile than the health of comparable women.

Across all missing data treatments, the interaction between initial functional limitations and household income exhibited a significant relationship with change in word-recall over time. For participants one standard deviation below the mean of household income, initial functional limitations were positively associated with the slope of word-recall, meaning for those with lower income, higher initial functional limitations reduced the rapidity at which word-recall scores declined across the observation period. Household income was positively associated with initial word-recall in all models, and negatively associated with initial number of functional limitations in two out of three models, indicating that those with lower household income may have experienced less dramatic cognitive decline due to the initial association between functional limitations and word-recall scores. Rather than indicating the significance of household income on the relationship between functional limitations and fluid memory, this finding highlights how lower income may influence the co-development of cognitive and functional health before the late adulthood, but with repercussions that unfold during the latest years of life.

As indicated by the relationship between cognitive health, functional limitations, and household income, the set of socioeconomic covariates tested here predicted a greater range of variation in the initial status of memory and physical function than change in either of these health measures. For example, those with less than a high school degree had significantly worse cognitive and functional health at baseline than their counterparts with a high school degree, but education was not significantly associated with change in these outcomes over time. For word-recall, only longest occupational tenure was significantly associated with change in word-recall, and this effect again reflected the lower initial word-recall of those with blue-collar occupation tenure as compared to white-collar occupation tenure. There were no measures of lifecourse SES consistently associated with change in functional limitations over time. These results indicate that disparities in cognitive and functional limitations are crystallized prior to the latest years of life and do not offer potential points of intervention to benefit the health of older adults. Indicators of lifecourse SES are by definition developed across the lifespan, and the constantly evolving construct of SES influences the development of cognitive and functional health across the lifecourse as well. The fact that disparities in these health outcomes are cemented before the latest years of life indicates that interventions to reduce socioeconomic disparities in cognitive and physical function among the elderly must focus on earlier points in life.

The findings of this study are strengthened by accounting for the potential biases introduced by mortality selection in longitudinal studies of aging. By comparing variation in estimates across traditional growth models and those with controls for NMAR data, effects that remain consistent across models can be taken as more trustworthy estimates, and the estimates produced here provide a strong reference point when examining other investigations of cognitive and functional trajectories that have not accounted for NMAR data. The variation in estimates across models is itself an interesting finding, indicating how each model attempts to control for observations NMAR. The DK model provided greater adjustments to the trajectories of the outcomes when compared to the traditional MAR model, and this likely results from the fact that the DK model employs dropout indicators that are endogenous to the growth process, in comparison to the pattern mixture model that employs dropout indicators exogenous to the growth process. The pattern mixture model produced baseline estimates of word-recall and functional limitations that were more advantageous than either the MAR or DK model, and likely indicates that those who were observed for greater amounts of time were given greater weight in the model, making the initial estimates of word-recall and functional limitations favor those who were initially healthier. These models incorporate a number of un-testable assumptions, and are certainly not a panacea for NMAR data, but provide a useful point of comparison for traditional growth models that do not account for the potential biases produced by mortality selection.

Limitations and future directions. While this research provides a number of insights into the contingent nature of cognitive and functional health in the socioeconomic context of aging, the modeling strategy employed restricted the potential questions that could be addressed. Greater examination of interactive effects between observed variables is warranted, especially between race/ethnicity and lifecourse SES, as research suggests that SES can mean substantially different things for those of different racial/ethnic backgrounds (Adler and Rehkopf 2008). Also, further decomposing the floor effects observed through careful examination of quadratic effects in the outcome trajectories could provide further insight into how trajectories of cognitive and functional health evolve, and what predictors influence change in these outcomes in the presence of controlling for non-linearity. Finally, further exploration of the interactions found between the latent and observed variables will provide more evidence of how SES can moderate the relationship between cognitive and functional health. This work provides a strong starting point from which a number of further investigations can be launched.

CHAPTER 6: CONCLUSION

With an increasing number of older individuals living to the latest points of the lifecourse, multiple institutions will be forced to account for the monetary and social costs that will accompany a graying population. The studies presented in this dissertation provide a number of methodological and substantive findings essential to the preparation for the aging of modern societies.

Specifically, the statistical methods used throughout these studies contribute to our understanding of how health-associated dropout can influence measuring health trajectories, and what can be done to account for biases introduced by non-random missing data. Second, this research examines the association between cognition, vascular health, and limitations in physical functioning. This exercise provides an understanding of how chronic disease co-morbidities influence the development of cognitive health among the aging, and in examining the co-development of cognitive and functional health, how cognition can be a precursor to later decreases in physical mobility. Finally, this work examines the relationship between chronic, vascular, and functional co-morbidities in the context of lifecourse socioeconomic status (SES) and race/ethnicity. Varying applications of these variables are used in the substantive portions of this research, but generally provide estimates of cognitive, vascular, and functional health adjusted for the social precursors of health and disease that act as fundamental determinants of health and quality of life in older adults. The methodological innovations, examinations of cognitive health and co-morbid chronic disease dynamics, and use of lifecourse SES in this research will each be thoroughly discussed, and this will be followed by a description of limitations and further elaborations that could strengthen future development of these research questions.

NMAR Data in Cognitive and Functional Trajectories

Those interested in the measurement of health trajectories in aging adults face the formidable task of understanding how parameter estimates of latent outcome variables and the effects of covariates are influenced by the NMAR data produced by mortality selection. While producing conservative bias in trajectories of cognition (Alwin, McCammon, Wray, and Rodgers 2008), the accurate measurement of individual trajectories is crucial to developing projections concerning the prevalence of chronic disease and health disparities in the future populations of older adults. The statistical techniques available to account for these biases are becoming more accessible to population health scientists, and this work provides an early example of the methodological foundation of these models and how these adjustments influence the measurement of cognitive and physical trajectories.

Parameter estimates provided by the Diggle-Kenward (DK) selection model, Wu-Carroll (WC) selection model, and the pattern mixture model each indicated that the initial level of word-recall was a significant predictor of likelihood of dropout in the AHEAD sample utilized in analyses. Both the WC and pattern mixture model consistently suggested that the trajectory of word-recall was associated with increased likelihood of dropout, but the DK model produced conflicting evidence of the association between cognitive trajectory and dropout. When investigating word-recall trajectories separately for white and black participants, the entire word-recall trajectory was associated with dropout for whites, but only initial cognitive function was a significant predictor of dropout for blacks. When examining the co-development of cognitive and physical health, initial limitations and increases in physical limitations over time were both positively associated with an increased chance of dropout in the study. These findings generally indicate the presence of NMAR data in the trajectories that were analyzed, and the need to account for this form of missing data to reduce potential biases in parameter estimates.

As an early example of NMAR methods in the literature on social gerontology/epidemiology, this research provides evidence of how NMAR adjustments can be employed in studies of health trajectories among the aged. The estimation of these models is becoming more accessible with common statistical packages, and hopefully this will allow researchers to produce new works employing these models to a number of different research questions. A major limitation of this work is the inability to compare the results produced by the NMAR models to other examples of similar work in the field. With the dissemination of these methods, we will be able to develop a better understanding of the assumptions behind these NMAR models, how these models adjust the estimated trajectories and effect of covariates, and how NMAR influences the measurement of change in a number of health outcomes. Importantly, wider use of these models will also allow us to understand where the use of these adjustments are not appropriate, and where they may produce greater biases than they alleviate. Greater use of NMAR adjustments to latent growth models will be essential to judge the true utility these methods provide.

Vascular and Physical Predictors of Cognitive Decline, in Socioeconomic Context

Both of the studies of co-morbid chronic diseases and cognitive health produced novel findings about how vascular and functional health are associated with individual cognitive trajectories. In the examination of the vascular hypothesis of cognitive health, specific cardiovascular risk factors were differentially associated with the cognitive health of white and black participants. Examining the co-development of cognitive and functional health produced evidence that cognition was a reliable precursor to change in functional health, while physical functioning was not consistently associated with change in cognitive health. Each of these studies found important interactions between the key health outcomes of interest and markers of lifecourse SES, pointing to the necessity of accounting for a diverse set of socioeconomic variables in studies of cognition and associated chronic diseases. The core findings of each study will be discussed separately, followed by description of the commonalities found across studies.

The substantive investigation of socioeconomic and racial/ethnic disparities in the relationship between cognitive trajectories and vascular diseases and their risk factors (VDRFs; Chapter 4) provides a portrait of vascular precursors of cognitive change tempered by controls for the social context where these comorbidities develop. This research found that VDRFs were differentially associated with cognitive outcomes for white and black individuals, with diabetes and heart problems each independently predicting change in word-recall scores for whites, and with diabetes influencing the cognitive health of blacks, but only through pathways associated with household assets and occupation. These findings support other work that observes socioeconomic and racial/ethnic variation in the prevalence of VDRFs. The racial/ethnic variation found in the relation between cognitive decline and VDRFs shows that those investigating vascular antecedents to cognitive decline must account for the social context where these related health measures are developed if accurate estimates of this relationship are to be produced.

In the examination of the co-development of cognitive and physical health presented in Chapter 5, cognitive functioning was found to consistently predict variation in later physical functioning, but the opposite was not found to be true. This work aligns with those who have found that cognitive health is a predecessor of functional health, but does not agree with findings that initial measures of cognition and physical function predict change in the alternate health process. The centrality of a healthy brain to physical functioning makes intuitive sense, and this work supports the notion that interventions aimed at maintaining healthy cognitive functioning will indirectly positively influence the maintenance of healthy physical function.

A number of similarities exist in the findings presented in these studies, including socioeconomic differentials in the association between cognition and the chronic diseases of interest, and the potential of floor effects producing the significant interactive terms that were found. Also, in both studies, lifecourse SES and race/ethnicity were able to predict relatively little variation in cognitive and functional trajectories, in comparison to baseline levels of these health outcomes.

In both substantive investigations, indicators of lifecourse SES moderated the effects of the health measures being used as predictors of cognitive trajectories. When testing the vascular hypothesis of cognitive aging, household assets and longest occupational tenure moderated the influence of diabetes on cognitive trajectory. For black diabetics, increasing household assets was associated with lower initial word-recall scores. In a similar fashion, black diabetics reporting longest occupational tenure in white-collar occupations had the highest word-recall scores initially, followed by the most rapid decline of all comparison groups. On the surface, the findings seem to indicate that for black diabetics, higher levels of SES are associated with relatively poor cognitive outcomes.

When studying the co-development of cognitive and functional health, initial number of functional limitations were differentially associated with change in word-recall based on household income. Those on the lower range of household income experienced benefits from a higher number of initial functional limitations, in terms of less rapid cognitive decline, than those with higher levels of household income. Again, this finding suggests those with greater access to socioeconomic resources had less advantageous memory trajectories than those with lower levels of SES. Based on the fundamentally positive association between SES and health found in practically all existing literature, conclusions of these interactive terms are better understood as artifacts of health and mortality selection associated with aging populations.

As populations advance into old age, access to socioeconomic resources, beginning in childhood and continuing throughout the lifecourse, influences the development of health and disease. Disparities in access to these health-enabling resources places individuals at differential risk of sickness and chronic disease. Understanding socioeconomic health disparities from a lifecourse perspective, those with restricted access to monetary and social resources throughout the lifecourse accumulate differential levels of the risk of developing health problems and experiencing mortality. The concept that variations in exposure to SES in early life produces divergent health outcomes in older ages is defined as the theory of cumulative disadvantage (Ross and Wu 1996), and is a central tenant of the lifecourse approach to social epidemiology (Berkman and Kawachi 2000). As this study explicitly examines individuals at the latest periods of the lifecourse, participants have had a lifetime of exposure to the benefits and risks determined by SES. With low status individuals getting sicker and experiencing mortality earlier than those with high status, those lucky enough to live to the ages of individuals included in the AHEAD study should be considered a select group. As mortality selection reduces heterogeneity in health between individuals in older age groups (Alwin 2009), it is expected that there will be less socioeconomic variation in health in the latest points of life. With this in mind, interpretation of significant interactions between comorbid chronic conditions and lifecourse SES found in this study are brought into a proper frame of reference.

For example, the association found between diabetes and household assets for blacks indicates that black diabetics who survive to the ages of those included in the analytic sample are a select group, with poor black diabetics being the most select subgroup of black individuals. Being black, having low income, and having diabetes place the individual at the intersection of a multitude of threats to health and survival, making those that can withstand these conditions healthier than comparable groups. Analogously, the finding that black white-collar diabetics have the most detrimental word-recall trajectories suggest that blacks with longest occupational tenure in white-collar employment settings were more susceptible to the negative effect of diabetes than white-collar blacks without diabetes, and all blacks who worked in blue-collar settings. Having not withstood the weathering of health associated with lower status occupations, having diabetes in late life was particularly detrimental for this group of individuals.

The association between baseline physical functioning, cognitive trajectories, and household income is another example of how the cumulative disadvantage associated with low SES influences the association between the chronic diseases central to this study. In all missing data treatments presented in Chapter 5, household income was positively associated with initial cognitive function, and was negatively associated with initial functional limitations in two of the three NMAR models. Initial functional limitations appears to protect low income individuals from rapid cognitive decline, but in actuality individuals with low income have lower cognitive abilities at baseline measurement, and have fewer cognitive abilities that can decline over time. Thus the relationship observed between initial functional limitations and cognitive decline is an artifact created by the low initial measures of cognitive and physical functioning.

The lifecourse approach to examining chronic health disparities also helps explain the consistent finding that indicators of lifecourse SES were better able to predict variation in initial cognitive and physical function than change in these measures over the decade of observation used in the study. As individuals in the baseline samples utilized here were around the age of 70, the majority of one's lifetime exposure to SES had occurred prior to observations in the AHEAD study. A number of indicators of SES were associated with baseline measurements of cognition and physical function, indicating that all prior exposures to SES influenced the levels of health these individuals displayed when first being measured. The ten years of observations analyzed here represent a relatively short amount of time for SES to produce variation in cognitive and functional outcomes, especially when compared to the seven decades of exposure to SES captured in the baseline observations of health. It is a common finding that initial levels of cognitive and functional limitations are more strongly associated with SES than the trajectories of these health outcomes (Anstey, Hofer, and Luszcz 2003; House, Lantz, and Herd 2005; Zimmer and House 2003). The results presented here contribute support to others who have found that socioeconomic disparities in health are developed across the lifecourse, and are thus crystallized prior to the latest years of life.

Limitations and Future Directions

While the studies presented here contribute to the progression of knowledge in the fields of social epidemiology, medical sociology, and social gerontology, there are a number of limitations to this research that need to be addressed.

First, a limitation of the NMAR models utilized here are the rudimentary missing data indicators employed to adjust the trajectories of interest. Further refinement of the missing data models should be developed through the estimation of separate adjustments for dropout due to mortality, institutionalization, and sporadic missingness. This study employed missing data indicators derived from the outcome variables themselves, meaning specific causes of dropout were not accounted for. The relationship between health trajectories and dropout caused by mortality and institutionalization are likely similar, where those with poor initial health and unfavorable health trajectories would both be more likely to exhibit dropout, either due to mortality or institutionalization. The similarity in the relationship between health trajectories and the causes of permanent dropout provides some justification for the coding of the missing data indicators used here, but the causal mechanisms behind these different sources of missing data warrant further investigation. Elaborations of this work will employ sources of information on dropout that will allow differential dropout mechanisms to be coded for those who experience mortality and those who drop out of the study due to institutionalization.

In terms of the chronic health co-morbidities and SES being examined here, limitations to this study include the accuracy of the variables employed. For the word-recall measure, test collectors had no control over an individual's access to materials such as pen and paper that would allow one to inflate their true ability to recall the words listed to them. Also, controls for test-retest effects were not included due to modeling issues associated with the controls for data NMAR. These issues could have biased the measurement of word-recall scores, making individuals appear to have better cognitive functioning than they truly had. The logistic of conducting a nationally representative sample of older Americans does not allow face-to-face interviews, but this would be a potential way to alleviate the biases allowed through phone interviews.

In examining the relationship between cognitive trajectories, co-morbid chronic diseases, and lifecourse SES, further examinations utilizing different measures of each of these three sets of variables would provide a more robust portrait of cognitive decline in late adulthood. The AHEAD study includes a multitude of proxies for cognitive functioning, including measures from the widely used Mini-Mental Status Examination (MMSE) and the Telephone Interview for Cognitive Status (TICS), which are both designed to capture individuals' overall cognitive function. The word-recall task is a specific indicator of working memory and fluid cognitive abilities, and this was chosen as an indicator sensitive to change in old age. Confirming the findings of the methodological and substantive portions of this dissertation using other indicators of cognitive status would provide useful information on how cognition, broadly defined, is associated with co-morbid chronic diseases and lifecourse SES.

The substantive questions addressed here focused on a relatively narrow set of co-morbid health indicators, namely vascular and functional health. For vascular health, individuals were asked to report if they had been doctor diagnosed with the given vascular health problem. This is problematic in that under-diagnoses of these vascular conditions likely varies by severity of condition, access to health services, and therefore SES. A number of individuals may have been diabetic, although they had never been diagnosed with diabetes. The use of clinical measures of VDRFs would provide these analyses strength, and could reduce potential biases inherent in the self-report of doctor diagnoses utilized here.

The measure of functional health used in examining the co-development of cognitive and functional health provides a measure of basic physical abilities that reduces the potential influence of SES, but fewer studies utilize this measure as compared to the widely-used activities of daily living scale (ADLs). Conducting the analyses presented in Chapter 5 with a wider-set of indicators of cognitive and functional outcomes would help harmonize the findings of this study with more research, and could provide evidence of nuances in the relationship between cognitive and functional health, simply caused by choosing different indicators of these health outcomes.

The set of measures used to assess lifecourse SES were carefully chosen, and did provide a proxy of SES that captures access to socioeconomic resources across the lifecourse. Measuring social mobility across the lifecourse, and using this to predict cognitive trajectories, would be a strong elaboration of this work. Also, approaching these analyses from a dyadic perspective would provide a portrait of how a spouse's lifecourse SES could influence the development of an individual's cognitive health in late old age. Measures of assets and monetary income used in these studies were measured at the household level, but the childhood SES, education, and longest occupational tenure of a spouse may have a strong influence on the socioeconomic resources an individual has access to. By incorporating measures of social mobility and spousal lifecourse SES, this work could more thoroughly account for the socioeconomic context where individuals and their health develop.

The limitations of this study are better cast as opportunities, because each drawback discussed provides a fruitful direction to continue this research. The modeling strategies and variables employed here were carefully chosen, providing a solid foundation for further examinations of cognitive functioning in old age to be constructed. The works presented here represent an early attempt at synthesizing novel statistical models that can address measurement issues common to studies of health trajectories among the aged with dominant theories of lifecourse SES taken from medical sociology and social epidemiology. In this sense, the modeling strategy and theoretical background provided here can be mapped on to any study of older adults examining health trajectories. The influence of mortality selection on accuracy of measurement, and the role of lifecourse SES in the production of cumulative advantage/disadvantage in older age should be present in all examinations of health trajectories among the aged, and this study provides an example that can be used by a wide range of social scientists in the development of their own research questions.

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Table 1. Weighted Descriptive Statistics for Variables included in Chapter 5

	White			Black		
	Mean	%	SD	Mean	%	SD
Total Word-Recall 1998	8.46		3.68	6.52		3.62
Total Word-Recall 2000	8.18		3.51	6.67		3.23
Total Word-Recall 2002	7.95		3.45	6.61		3.37
Total Word-Recall 2004	7.62		3.23	6.08		3.08
Total Word-Recall 2006	7.37		3.24	5.90		3.05
Total Word-Recall 2008	7.19		3.34	5.42		3.19
Age	79.20		5.54	79.77		5.87
Female		65.22			70.27	
Married		52.50			32.49	
Years of Education	12.04		2.86	9.19		3.97
Household Income ($)			41,894.96			20,203.83
Household Assets ($)			811,641.89			132,570.27
White-Collar Job Tenure		44.36			20.36	
Blue-Collar Job Tenure		26.94			57.12	
Homemaker Job Tenure		9.58			3.78	
Other Job Tenure		19.13			18.74	
Mother > = 8 yrs. Education		61.20			41.70	
Father > = 8 yrs. Education		57.10			34.70	
Favorable Childhood Circum.		68.70			56.00	
Father White-Collar		25.30			8.30	
Diagnosed with Hypertension		54.20			70.60	
Diagnosed with Diabetes		14.00			24.00	
Diagnosed with Heart Problems		31.70			24.50	
Diagnosed with Stroke		9.31			8.56	

Note: White N = 3,979, Black N = 555.

Table 2. Weighted Descriptive Statistics for Variables included in Chapter 6

	Mean	%	SD	% Present	% Dropout
Word-Recall and Functional Limitations					
Total Word-Recall 1998	8.45		3.72	100	
Total Word-Recall 2000	7.79		3.61	80.96	19.04
Total Word-Recall 2002	7.28		3.57	66.47	33.53
Total Word-Recall 2004	6.70		3.44	53.64	46.36
Total Word-Recall 2006	6.10		3.45	42.55	57.45
Total Word-Recall 2008	5.73		3.61	32.67	67.33
Functional Limitations 1998	3.02		2.91	100	
Functional Limitations 2000	3.44		3.05	85.92	14.08
Functional Limitations 2002	4.14		3.15	72.51	27.49
Functional Limitations 2004	4.54		3.27	60.11	39.89
Functional Limitations 2006	5.38		3.43	48.31	51.69
Functional Limitations 2008	5.71		3.47	36.54	63.46

Note: N = 4,653; all estimates averaged over 20 imputed data sets.

Table 2 (Continued). Weighted Descriptive Statistics for Variables included in Chapter 6

		Mean	%	SD	% Present	% Dropout
Independent Variables						
Age		79.13		5.31		
White			89.90			
Black			6.40			
Hispanic			3.70			
Female			65.60			
Married			49.30			
White-Collar Occupation Tenure			41.70			
Blue-Collar Occupation Tenure			29.80			
Homemaker Occupation Tenure			9.10			
Other Occupation Tenure			19.40			
Less than H.S. Degree			33.10			
H.S. Degree			35.10			
Greater than H.S. Degree			31.80			
Household Income	($)	31,144.68		39,663.97		
Household Assets	($)	280,441.80		75,7295.40		
Mother > = 8 yrs. Education			59.40			
Father > = 8 yrs. Education			54.80			
Father White-Collar			23.90			

Note: N = 4,653; all estimates averaged over 20 imputed data sets.

Table 3. Missing Data Patterns and Frequencies in AHEAD Study, 1998 - 2008

	Observation Period								
Pattern	1998	2000	2002	2004	2006	2008	Frequency	Percentage	Cumulative Percentage
1	X	X	X	X	X	X	1374	28.77	28.77
2	X	X	X	X	X		393	8.23	37.00
3	X	X	X	X			459	9.61	46.61
4	X	X	X				582	12.19	58.79
5	X	X					700	14.66	73.45
6	X						934	19.56	93.01
7	X	X	X	X		X	42	0.88	93.89
8	X	X	X		X	X	25	0.52	94.41
9	X	X	X		X		26	0.54	94.95
10	X	X	X			X	13	0.27	95.23
11	X	X		X	X	X	25	0.52	95.75
12	X	X		X	X		14	0.29	96.04
13	X	X		X		X	1	0.02	96.06
14	X	X		X			31	0.65	96.71
15	X	X			X	X	8	0.17	96.88

Note: N = 4,776; X = observed

Table 3 (Continued). Missing Data Patterns and Frequencies in AHEAD Study, 1998 - 2008

	Observation Period								
Pattern	1998	2000	2002	2004	2006	2008	Frequency	Percentage	Cumulative Percentage
17	X	X				X	5	0.10	97.09
18	X		X	X	X	X	18	0.38	97.47
19	X		X	X	X		12	0.25	97.72
20	X		X	X		X	2	0.04	97.76
21	X		X	X			23	0.48	98.24
22	X		X		X	X	2	0.04	98.28
23	X		X		X		3	0.06	98.35
24	X		X			X	1	0.02	98.37
25	X		X				36	0.75	99.12
26	X			X	X	X	7	0.15	99.27
27	X			X	X		4	0.08	99.35
28	X			X			13	0.27	99.62
29	X				X	X	6	0.13	99.75
30	X				X		7	0.15	99.90
31	X					X	5	0.10	100.00

Note: N = 4,776; X = observed

Table 4. Observed and Estimated Word-Recall Trajectories from MAR and NMAR Models

			Observation Period					
	Intercept	Slope	1998	2000	2002	2004	2006	2008
Observed Mean Trajectory			8.41	7.85	7.36	6.84	6.28	5.90
MAR Estimated Trajectory	8.39	-2.59	8.39	7.87	7.36	6.84	6.32	5.80
DK Estimated Trajectory	8.37	-3.02	8.37	7.77	7.16	6.56	5.95	5.35
WC Estimated Trajectory	8.45	-4.23	8.45	7.61	6.76	5.92	5.07	4.23
PMM Estimated Trajectory	9.86	-2.70	9.86	9.32	8.78	8.24	7.70	7.16

Note: N = 4,776

Table 5. Estimates from NMAR model parameters (Chapter 4)

Wu-Carroll Selection Model		
	b	*SE*
Intercept	-0.38***	(0.02)
Slope	-0.43***	(0.04)
Loglikelihood	-52361.579	
Parameters	18	
BIC	104875.643	
Diggle-Kenward Selection Model		
	b	*SE*
Word-Recall t	-0.12***	(0.04)
Word-Recall $t - 1$	-0.15***	(0.03)
Level Word-Recall	-0.13***	(0.01)
Increment Word-Recall	0.02	(0.03)
Loglikelihood	-52345.529	
Parameters	18	
BIC	104843.542	
Pattern Mixture Model		
Intercept	*b*	*SE*
Dropout 2000	-3.61***	(0.16)
Dropout 2002	-2.34***	(0.17)
Dropout 2004	-1.77***	(0.17)
Dropout 2006	-1.33***	(0.18)
Dropout 2008	-0.58***	(0.19)
Slope	*b*	*SE*
Dropout 2000 - 2002	-3.90***	(0.72)
Dropout 2004	-1.70***	(0.31)
Dropout 2006	-1.67***	(0.25)
Dropout 2008	-2.37***	(0.38)
Loglikelihood	-53515.352	
Parameters	25	
BIC	107242.488	

Note: N = 4,776; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6. Parameter Estimates from Missing at Random and Not Missing at Random Latent Growth Models (Chapter 4)

	Missing at Random				Diggle-Kenward Selection Model			
			95% CI				95% CI	
Intercept	*b*	SE	Lower	Upper	*b*	SE	Lower	Upper
Intercept	7.71***	(.08)	7.55	7.87	7.66***	(.08)	7.49	7.82
Age	-0.22***	(.01)	-0.23	-0.20	-0.22***	(.01)	-0.24	-0.20
Female	1.15***	(.10)	0.95	1.35	1.18***	(.10)	0.98	1.38
Black	-0.97***	(.15)	-1.26	-0.67	-1.03***	(.15)	-1.32	-0.73
Hispanic	-0.71***	(.23)	-1.17	-0.25	-0.72***	(.23)	-1.19	-0.25
Education (years)	0.27***	(.02)	0.24	0.30	0.28***	(.02)	0.25	0.31
R-Squared		0.35				0.35		
Slope								
Slope	-2.32***	(.13)	-2.59	-2.05	-3.58***	(.20)	-3.97	-3.18
Age	-0.02	(.02)	-0.05	0.01	-0.11***	(.02)	-0.15	-0.08
Female	-0.75***	(.16)	-1.07	-0.42	-0.61***	(.17)	-0.95	-0.26
Black	0.18	(.25)	-0.32	0.68	0.28	(.26)	-0.23	0.80
Hispanic	0.57	(.38)	-0.19	1.33	0.72†	(.40)	-0.08	1.53
Education (years)	-0.05†	(.03)	-0.10	0.00	-0.04	(.03)	-0.10	0.02
R-Squared		0.03				0.06		
Intercept and Slope Covariance	-2.18 ***	(.35)	-2.87	-1.49	-1.88 ***	(.36)	-2.59	-1.17

Note: N = 4,776; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6 (Continued). Parameter Estimates from Missing at Random and Not Missing at Random Latent Growth Models (Chapter 4)

	Wu-Carroll Selection Model				Pattern Mixture Model			
			95% CI				95% CI	
Intercept	*b*	SE	Lower	Upper	*b*	SE	Lower	Upper
Intercept	7.83***	(.08)	7.67	7.99	8.70***	(.10)	8.50	8.90
Age	-0.21***	(.01)	-0.23	-0.19	-0.16***	(.01)	-0.18	-0.15
Female	1.10***	(.10)	0.90	1.30	0.99***	(.10)	0.80	1.19
Black	-1.02***	(.14)	-1.31	-0.74	-0.88***	(.14)	-1.16	-0.60
Hispanic	-0.74***	(.23)	-1.20	-0.29	-0.75***	(.22)	-1.20	-0.30
Education (years)	0.28***	(.02)	0.25	0.31	0.25***	(.02)	0.22	0.28
R-Squared	0.35				-			
Slope								
Slope	-4.24***	(.17)	-4.58	-3.90	-2.22***	(.15)	1.92	2.52
Age	-0.14***	(.01)	-0.16	-0.11	0.00	(.02)	-0.04	0.03
Female	-0.22	(.15)	-0.52	0.09	-0.67***	(.16)	-0.99	-0.35
Black	0.21	(.20)	-0.19	0.61	0.00	(.25)	-0.50	0.50
Hispanic	0.71*	(.32)	0.07	1.35	0.50	(.36)	-0.22	1.22
Education (years)	-0.05*	(.02)	-0.09	0.00	-0.05†	(.03)	-0.10	0.01
R-Squared	0.09				-			
Intercept and Slope Covariance	-1.13 ***	(.33)	-1.79	-0.47	-2.17 ***	(.33)	-2.83	-1.52

Note: N = 4,776; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 7. Estimates and Fit Statistics from MAR and NMAR Models from Chapter 5

	Traditional MAR Model			
	White		Black	
Loglikelihood	-37103.09		-4316.06	
Parameters	45		45	
BIC	74579.17		8916.47	
	Wu-Carroll Selection Model			
	White		Black	
Dropout	*b*	*SE*	*b*	*SE*
Intercept	-0.32***	(0.02)	-0.40***	(0.07)
Slope	-0.61***	(0.08)	-0.45†	(0.26)
Loglikelihood	-43405.38		-5206.57	
Parameters	51		51	
BIC	87233.487		10735.42	
	Diggle-Kenward Selection Model			
	White		Black	
Dropout	*b*	*SE*	*b*	*SE*
Word-Recall $t-1$	-0.01**	(0.00)	-0.01	(0.01)
Word-Recall	-0.05***	(0.00)	-0.05***	(0.01)
Loglikelihood	-43046.13		-5172.67	
Parameters	77		77	
BIC	86730.49		10831.90	
	Pattern-Mixture Model			
	White		Black	
Intercept	*b*	*SE*	*b*	*SE*
Dropout 2000	-2.06***	(0.18)	-2.92***	(0.34)
Dropout 2002	-1.17***	(0.18)	-2.04***	(0.42)
Dropout 2004	-0.94***	(0.17)	-1.59***	(0.37)
Dropout 2006	-0.67***	(0.18)	-2.07***	(0.53)
Dropout 2008	-0.15	(0.18)	-0.66	(0.47)
Slope				
Dropout 2000 – 2002	-4.71***	(0.79)	2.11	(1.89)
Dropout 2004	-2.63***	(0.42)	0.34	(0.97)
Dropout 2006	-1.88***	(0.27)	-1.16	(0.63)
Dropout 2008	-1.72***	(0.42)	-0.73	(0.87)
Loglikelihood	-36841.30		-4271.33	
Parameters	54		54	
BIC	74130.19		8883.88	

Note: White N = 3,979, Black N = 555; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 8. Maximum Likelihood Estimates of Socioeconomic and Vascular Predictors of Word-Recall Trajectories for Whites from MAR and NMAR Models

	MAR		WC		DK		PM	
Intercept	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Latent Intercept	8.26***	(0.19)	8.39***	(0.18)	8.41***	(0.18)	9.04***	(0.20)
Age	-0.22***	(0.01)	-0.21***	(0.01)	-0.23***	(0.01)	-0.17***	(0.01)
Female	1.11***	(0.13)	1.01***	(0.12)	1.08***	(0.12)	0.96***	(0.12)
Married	-0.42***	(0.13)	-0.42***	(0.12)	-0.44***	(0.13)	-0.39**	(0.12)
Years of Education	0.17***	(0.02)	0.19***	(0.02)	0.14***	(0.02)	0.16***	(0.02)
Household Income	0.17*	(0.08)	0.13†	(0.08)	0.19*	(0.09)	0.13†	(0.08)
Household Assets	0.10***	(0.02)	0.08***	(0.02)	0.11***	(0.02)	0.08***	(0.02)
Blue-Collar	-0.57***	(0.15)	-0.50***	(0.14)	-0.51***	(0.14)	-0.55***	(0.14)
Homemaker	-0.69***	(0.19)	-0.69***	(0.18)	-0.62***	(0.18)	-0.63***	(0.18)
Other Occ.	-0.15	(0.15)	-0.11	(0.14)	-0.18	(0.14)	-0.14	(0.15)
Mother > = 8 yrs. Education	0.35*	(0.15)	0.34*	(0.14)	0.29*	(0.14)	0.33*	(0.14)
Father > = 8 yrs. Education	-0.08	(0.14)	-0.11	(0.13)	-0.02	(0.13)	-0.09	(0.14)
Favorable Childhood Circum.	-0.12	(0.12)	-0.08	(0.11)	-0.17	(0.11)	-0.05	(0.11)
Father White-Collar	0.27†	(0.14)	0.29*	(0.13)	0.24†	(0.13)	0.25†	(0.13)
Diagnosed with Hypertension	-0.04	(0.11)	-0.02	(0.10)	-0.03	(0.10)	-0.02	(0.10)
Diagnosed with Diabetes	-0.08	(0.15)	-0.04	(0.14)	-0.21	(0.15)	0.08	(0.15)
Diagnosed with Heart Problems	-0.06	(0.12)	0.04	(0.11)	-0.18	(0.12)	0.06	(0.11)
Diagnosed with Stroke	-0.77***	(0.18)	-0.75***	(0.17)	-0.87***	(0.19)	-0.54**	(0.17)
R-Squared	0.36***	(.02)	0.37***	(0.02)	0.36***	(0.02)	0.41***	(.02)
BIC	74579.17		87233.49		86730.49		74130.19	

Note: White N = 3,979; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 8 (Continued). Maximum Likelihood Estimates of Socioeconomic and Vascular Predictors of Word-Recall Trajectories for Whites from MAR and NMAR Models

	MAR		WC		DK		PM	
Slope	*b*	*SE*	*b*	*SE*	*b*	*SE*	*B*	*SE*
Latent Slope	-2.58***	(0.30)	-3.75***	(0.27)	-4.81***	(0.53)	-2.42***	(0.31)
Age	-0.02	(0.02)	-0.11***	(0.01)	-0.19***	(0.04)	0.00	(0.02)
Female	-0.64**	(0.21)	-0.10	(0.19)	-0.17	(0.25)	-0.58**	(0.20)
Married	0.28	(0.20)	0.28†	(0.16)	0.25	(0.23)	0.22	(0.20)
Years of Education	0.03	(0.04)	-0.02	(0.03)	0.09†	(0.05)	0.03	(0.04)
Household Income	-0.14	(0.12)	0.02	(0.09)	-0.04	(0.13)	-0.13	(0.12)
Household Assets	-0.05	(0.04)	0.02	(0.03)	0.02	(0.05)	-0.06	(0.04)
Blue-Collar	0.47*	(0.23)	0.16	(0.19)	0.27	(0.25)	0.50*	(0.23)
Homemaker	0.23	(0.31)	0.17	(0.24)	-0.05	(0.35)	0.21	(0.30)
Other Occ.	0.24	(0.25)	0.08	(0.19)	0.17	(0.28)	0.25	(0.24)
Mother >= 8 yrs. Education	-0.10	(0.23)	-0.04	(0.18)	0.03	(0.26)	-0.11	(0.23)
Father >= 8 yrs. Education	-0.07	(0.22)	0.04	(0.17)	-0.08	(0.24)	-0.06	(0.21)
Favorable Childhood Circum.	-0.07	(0.19)	-0.29*	(0.14)	-0.27	(0.21)	-0.03	(0.19)
Father White-Collar	0.04	(0.23)	-0.04	(0.18)	0.12	(0.25)	0.04	(0.22)
Diagnosed with Hypertension	-0.06	(0.17)	-0.09	(0.13)	-0.17	(0.19)	0.00	(0.17)
Diagnosed with Diabetes	-0.42	(0.26)	-0.76***	(0.20)	-0.88**	(0.32)	-0.35	(0.25)
Diagnosed with Heart Problems	0.08	(0.21)	-0.42**	(0.15)	-0.23	(0.24)	0.11	(0.20)
Diagnosed with Stroke	-0.21	(0.37)	-0.64*	(0.26)	-0.97*	(0.47)	-0.21	(0.36)
R-Squared	0.04**	(0.02)	0.14***	(.02)	0.15***	(0.03)	0.422***	(0.08)
BIC	74579.17		87233.49		86730.49		74130.19	

Note: White N = 3,979; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 9. Maximum Likelihood Estimates of Socioeconomic and Vascular Predictors of Word-Recall Trajectories for Blacks from MAR and NMAR Models

	MAR		WC		DK		PM	
Intercept	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Latent Intercept	7.47***	(0.47)	7.61***	(0.45)	7.49***	(0.47)	8.83***	(0.45)
Age	-0.17***	(0.02)	-0.17***	(0.03)	-0.18***	(0.03)	-0.11***	(0.02)
Female	0.83**	(0.28)	0.76*	(0.31)	0.81**	(0.29)	0.47†	(0.28)
Married	-0.40	(0.32)	-0.42	(0.33)	-0.52	(0.32)	-0.36	(0.30)
Years of Education	0.24***	(0.04)	0.25***	(0.04)	0.25***	(0.04)	0.23***	(0.03)
Household Income	0.11	(0.28)	0.14	(0.29)	0.10	(0.28)	0.14	(0.24)
Household Assets	0.02	(0.03)	0.02	(0.03)	0.03	(0.03)	0.02	(0.02)
Blue-Collar	-0.96*	(0.40)	-0.91*	(0.39)	-0.97*	(0.40)	-0.93*	(0.37)
Homemaker	-1.65**	(0.59)	-1.64**	(0.58)	-1.58**	(0.61)	-1.55**	(0.56)
Other Occ.	-1.09*	(0.52)	-1.09*	(0.49)	-1.18*	(0.52)	-0.79	(0.49)
Mother > = 8 yrs. Education	-0.22	(0.34)	-0.28	(0.33)	-0.22	(0.35)	-0.34	(0.32)
Father > = 8 yrs. Education	0.24	(0.34)	0.30	(0.34)	0.16	(0.35)	0.31	(0.32)
Favorable Childhood Circum.	-0.46†	(0.25)	-0.43†	(0.25)	-0.49†	(0.25)	-0.36	(0.24)
Father White-Collar	-0.12	(0.58)	-0.17	(0.59)	-0.29	(0.59)	-0.02	(0.54)
Diagnosed with Hypertension	0.04	(0.29)	0.05	(0.28)	0.01	(0.28)	0.13	(0.26)
Diagnosed with Diabetes	-0.41	(0.31)	-0.39	(0.31)	-0.38	(0.31)	-0.11	(0.29)
Diagnosed with Heart Problems	-0.20	(0.30)	-0.19	(0.29)	-0.20	(0.31)	-0.04	(0.28)
Diagnosed with Stroke	-0.61	(0.46)	-0.52	(0.45)	-0.60	(0.48)	-0.37	(0.42)
R-Squared	0.43 ***	(0.05)	0.52 ***	(0.05)	0.42 ***	(0.05)	0.56	(0.05)
BIC	8916.47		10735.42		10831.90		8883.88	

Note: Black N = 555; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 9 (Continued). Maximum Likelihood Estimates of Socioeconomic and Vascular Predictors of Word-Recall Trajectories for Blacks from MAR and NMAR Models

	MAR		WC		DK		PM	
Slope	*b*	*SE*	*b*	*SE*	*b*	*SE*	*B*	*SE*
Latent Slope	-2.48**	(0.78)	-3.55***	(0.75)	-4.26**	(1.53)	-3.39***	(0.80)
Age	0.00	(0.05)	-0.07	(0.04)	-0.11	(0.07)	-0.04	(0.05)
Female	-0.74	(0.49)	-0.37	(0.62)	-0.12	(0.58)	-0.53	(0.50)
Married	0.00	(0.51)	0.17	(0.47)	-0.09	(0.50)	0.01	(0.50)
Years of Education	-0.07	(0.07)	-0.14*	(0.06)	-0.10	(0.09)	-0.06	(0.07)
Household Income	0.27	(0.31)	0.14	(0.31)	0.21	(0.27)	0.24	(0.29)
Household Assets	-0.06	(0.05)	-0.04	(0.05)	-0.04	(0.05)	-0.07	(0.05)
Blue-Collar	0.87	(0.62)	0.76	(0.56)	0.79	(0.62)	0.90	(0.61)
Homemaker	1.67	(1.09)	1.85*	(0.88)	1.49	(1.04)	1.57	(1.07)
Other Occ.	0.41	(0.94)	0.43	(0.78)	0.17	(0.98)	0.17	(0.94)
Mother > = 8 yrs. Education	-0.04	(0.53)	0.35	(0.46)	0.37	(0.52)	0.02	(0.51)
Father > = 8 yrs. Education	0.25	(0.60)	-0.19	(0.53)	0.16	(0.60)	0.22	(0.58)
Favorable Childhood Circum.	0.41	(0.44)	0.26	(0.41)	0.11	(0.42)	0.40	(0.43)
Father White-Collar	-0.98	(0.98)	-0.93	(0.97)	-0.87	(1.07)	-1.15	(0.97)
Diagnosed with Hypertension	0.10	(0.47)	0.01	(0.39)	0.05	(0.45)	-0.01	(0.46)
Diagnosed with Diabetes	-0.55	(0.54)	-0.57	(0.54)	-0.83	(0.56)	-0.71	(0.54)
Diagnosed with Heart Problems	-0.44	(0.56)	-0.47	(0.46)	-0.70	(0.58)	-0.47	(0.54)
Diagnosed with Stroke	0.25	(0.80)	-0.61	(0.76)	-0.32	(0.96)	0.02	(0.78)
R-Squared	-2.48 **	(.78)	-3.55 ***	(0.75)	-4.26 **	(1.53)	-3.39 ***	(0.80)
BIC	8916.47		10735.42		10831.90		8883.88	

Note: Black N = 555; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 10. Maximum Likelihood Estimates of Interactive Effects between Socioeconomic Status and Vascular Health in Word-Recall Trajectories for Blacks from MAR and NMAR Models

Missing Data Model	MAR		WC		DK		PM	
Intercept	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Latent Intercept	7.27 ***	(0.49)	7.40 ***	(0.48)	7.33 ***	(0.48)	8.63 ***	(0.46)
Age	-0.17 ***	(0.02)	-0.16 ***	(.030)	-0.17 ***	(0.03)	-0.11 ***	(0.02)
Female	0.86 **	(0.28)	0.81 **	(0.30)	0.84 **	(0.29)	0.50 †	(0.27)
Married	-0.43	(0.32)	-0.43	(0.32)	-0.56 †	(0.32)	-0.40	(0.30)
Years of Education	0.24 ***	(0.04)	0.26 ***	(0.04)	0.25 ***	(0.04)	0.24 ***	(0.03)
Household Income	0.12	(0.28)	0.13	(0.28)	0.11	(0.28)	0.15	(0.24)
Household Assets	0.07 **	(0.03)	0.07 *	(0.03)	0.09 **	(0.03)	0.06 *	(0.03)
Blue-Collar	-0.60	(0.43)	-0.57	(0.42)	-0.65	(0.42)	-0.61	(0.40)
Homemaker	-1.74 **	(0.59)	-1.75 **	(0.57)	-1.70 **	(0.61)	-1.64 **	(0.57)
Other Occ.	-1.04 *	(0.51)	-1.05 *	(0.50)	-1.15 *	(0.51)	-0.77	(0.48)
Mother > = 8 yrs. Education	-0.22	(0.32)	-0.27	(0.31)	-0.22	(0.33)	-0.35	(0.30)
Father > = 8 yrs. Education	0.24	(0.35)	0.28	(0.34)	0.16	(0.35)	0.34	(0.32)
Favorable Childhood Circum.	-0.52 *	(0.25)	-0.51 *	(0.25)	-0.55 *	(0.25)	-0.41 †	(0.23)
Father White-Collar	-0.14	(0.57)	-0.18	(0.57)	-0.30	(0.58)	-0.07	(0.53)
Diagnosed with Hypertension	0.00	(0.28)	0.00	(0.28)	-0.02	(0.28)	0.10	(0.26)
Diagnosed with Diabetes	0.32	(.051)	0.32	(0.53)	0.26	(0.51)	0.53	(0.48)
Diagnosed with Heart Problems	-0.16	(0.3)	-0.16	(0.30)	-0.17	(0.31)	0.00	(0.29)
Diagnosed with Stroke	-0.58	(0.46)	-0.50	(0.45)	-0.52	(0.48)	-0.35	(0.42)
HH Assets * Diabetes	-0.17 **	(0.06)	-0.17 ***	(0.05)	-0.19 ***	(0.06)	-0.16 **	(0.05)
Blue-Collar Occ.* Diabetes	-1.25 †	(0.64)	-1.21 †	(0.66)	-1.11 †	(0.66)	-1.12 †	(0.59)
R-Squared	0.45 ***	(0.05)	0.54 ***	(0.05)	0.44 ***	(0.05)	0.57 ***	(0.05)
BIC	8922.13		10738.10		10837.56		8890.42	

Note: Black N = 555; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 10 (Continued). Maximum Likelihood Estimates of Interactive Effects between Socioeconomic Status and Vascular Health in Word-Recall Trajectories for Blacks from MAR and NMAR Models

Missing Data Model	MAR		WC		DK		PM	
Slope	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Latent Slope	-1.99 *	(0.81)	-3.06 ***	(0.86)	-3.80 *	(1.55)	-2.88 ***	(0.81)
Age	0.00	(0.05)	-0.07	(0.04)	-0.11	(0.07)	-0.04	(0.05)
Female	-0.85 †	(0.50)	-0.56	(0.61)	-0.26	(0.59)	-0.66	(0.50)
Married	0.15	(0.51)	0.25	(0.45)	0.05	(0.50)	0.16	(0.49)
Years of Education	-0.07	(0.07)	-0.14 *	(0.06)	-0.09	(0.09)	-0.06	(0.07)
Household Income	0.21	(0.29)	0.13	(0.27)	0.15	(0.26)	0.19	(0.28)
Household Assets	-0.10 †	(0.06)	-0.10 †	(0.05)	-0.08	(0.06)	-0.11 *	(0.06)
Blue-Collar	0.14	(0.67)	0.11	(0.62)	0.14	(0.68)	0.21	(0.66)
Homemaker	1.56	(1.13)	1.83 *	(0.89)	1.41	(1.10)	1.49	(1.10)
Other Occ.	0.43	(0.91)	0.44	(0.82)	0.19	(0.95)	0.21	(0.91)
Mother > = 8 yrs. Education	-0.10	(0.55)	0.31	(0.49)	0.34	(0.55)	-0.02	(0.54)
Father > = 8 yrs. Education	0.09	(0.59)	-0.32	(0.51)	-0.06	(0.57)	0.02	(0.58)
Favorable Childhood Circum.	0.53	(0.44)	0.42	(0.43)	0.22	(0.43)	0.53	(0.43)
Father White-Collar	-0.96	(0.97)	-0.88	(0.96)	-0.72	(1.09)	-1.11	(0.96)
Diagnosed with Hypertension	0.11	(0.46)	0.04	(0.41)	0.05	(0.45)	0.00	(0.46)
Diagnosed with Diabetes	-2.26 *	(0.94)	-2.23 *	(1.10)	-2.41 *	(1.03)	-2.32 *	(0.93)
Diagnosed with Heart Problems	-0.43	(0.55)	-0.43	(0.49)	-0.70	(0.59)	-0.44	(0.53)
Diagnosed with Stroke	0.15	(0.78)	-0.64	(0.77)	-0.41	(0.94)	-0.07	(0.75)
HH Assets * Diabetes	0.10	(0.12)	0.13	(0.11)	0.09	(0.13)	0.11	(0.12)
Blue-Collar Occ.* Diabetes	2.96 *	(1.17)	2.78 *	(1.32)	2.73 *	(1.20)	2.81 *	(1.14)
R-Squared	0.21 **	(0.07)	0.45 ***	(0.11)	0.20 *	(0.09)	0.34 †	(0.18)
BIC	8922.13		10738.10		10837.56		8890.42	

Note: Black N = 555; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model.

Table 11. Estimates from NMAR Model Parameters for Word-Recall and Functional Limitation Trajectories

Diggle-Kenward Selection Model		
	b	*SE*
Word-Recall *t* - 1	0.16***	(0.02)
Word-Recall *t*	-0.76***	(0.05)
Level Word-Recall	-0.30***	(0.02)
Increment Word-Recall	-0.46***	(0.04)
Functional Limitations		
Functional Limitation *t* - 1	-0.15***	(0.02)
Functional Limitation *t*	0.46***	(0.03)
Level Functional Limitation	0.16***	(0.01)
Level Increment Functional Limitations	0.30***	(0.03)
Pattern-Mixture Model		
Word-Recall		
Intercept	*b*	*SE*
Dropout 2000	-2.18***	(0.16)
Dropout 2002	-1.72***	(0.15)
Dropout 2004	-1.06***	(0.16)
Dropout 2006	-0.77***	(0.17)
Dropout 2008	-0.15	(0.18)
Slope		
Dropout 2000 – 2002	-0.25	(0.48)
Dropout 2004	-2.32***	(0.39)
Dropout 2006	-1.77***	(0.31)
Dropout 2008	-1.66***	(0.25)
Functional Limitations		
Intercept	*b*	*SE*
Dropout 2000	1.99***	(0.15)
Dropout 2002	1.59***	(0.15)
Dropout 2004	1.01***	(0.15)
Dropout 2006	0.87***	(0.14)
Dropout 2008	0.34*	(0.15)
Slope		
Dropout 2000 - 2002	-0.25	(0.48)
Dropout 2004	2.37***	(0.36)
Dropout 2006	0.97***	(0.27)
Dropout 2008	0.82***	(0.20)

Note: N = 4,653; * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 12. Model Fit Statistics for MAR and NMAR Parallel Process Structural Models

	Model 1			Model 2		
	MAR	DK	PMM	MAR	DK	PMM
Free Parameters	24	38	51	25	39	52
Log-Likelihood	-86407.05	-100828.31	-103245.32	-86398.18	-100824.37	-103241.65
Akaike Information Criteria (AIC)	172862.10	201732.62	206592.63	172846.35	201726.74	206587.301
Bayesian Information Criteria (BIC)	173016.79	201977.54	206921.34	173007.48	201978.11	206922.46
Sample-Adjusted BIC	172940.53	201856.79	206759.28	172928.04	201854.18	206757.22

	Model 3			Model 4		
	MAR	DK	PMM	MAR	DK	PMM
Free Parameters	25	39	52	26	40	53
Log-Likelihood	-86390.34	-100762.89	-103222.89	**-86385.08**	**-100744.58**	**-103221.78**
Akaike Information Criteria (AIC)	172830.69	201603.77	206549.77	**172822.16**	**201569.15**	**206549.57**
Bayesian Information Criteria (BIC)	172991.82	201855.14	**206884.92**	**172989.73**	**201826.96**	206891.17
Sample-Adjusted BIC	172912.38	201731.21	**206719.69**	**172907.11**	**201699.86**	206722.75

Note: N = 4,653; MAR = missing at random, DK = Diggle-Kenward selection model, PMM = pattern mixture model; bold numbers indicate best model fit

Table 13. Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for MAR Data Model

	Word-Recall			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	8.13	(0.17)	-2.93	(0.28)
Latent Predictor Variables				
Intercept Word-Recall				
Intercept Functional Limitations			0.09*	(0.04)
Observed Predictor Variables				
Age	-0.22***	(0.01)	-0.03	(0.02)
Black	-0.82***	(0.16)	0.00	(0.27)
Hispanic	-0.93***	(0.23)	0.50	(0.37)
Female	1.12***	(0.12)	-0.72***	(0.20)
Married	-0.44***	(0.12)	0.22	(0.19)
Blue-Collar Occ. Tenure	-0.64***	(0.14)	0.52**	(0.22)
Homemaker Occ. Tenure	-0.63***	(0.18)	(0.11	(0.29)
Other Occ. tenure	-0.20	(0.15)	0.10	(0.24)
< H.S. Degree	-0.68***	(0.13)	-0.03	(0.22)
> H.S. Degree	0.41***	(0.13)	0.11	(0.21)
H.H. Income (log)	0.21***	(0.08)	-0.08	(0.10)
H.H. Assets (log)	0.10***	(0.02)	-0.04	(0.03)
Mother >= 8 yrs. Education	0.33**	(0.13)	-0.08	(0.21)
Father > = 8 yrs. Education	-0.04	(0.13)	-0.04	(0.21)
Father White-Collar Occ. Tenure	0.27*	(0.13)	0.06	(0.21)
R-Squared	0.37		0.05	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 13 (Continued). Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for MAR Data Model

	Functional Limitations			
	Intercept		Intercept	
	b	*SE*	*b*	*SE*
Intercepts	2.41	(0.15)	3.70	(0.40)
Latent Predictor Variables				
Intercept Word-Recall			-0.08*	(0.04)
Intercept Functional Limitations				
Observed Predictor Variables				
Age	0.08***	(0.01)	0.10***	(0.02)
Black	-0.15	(0.16)	0.06	(0.24)
Hispanic	-0.66***	(0.22)	0.19	(0.36)
Female	0.75***	(0.10)	-0.10	(0.16)
Married	0.14	(0.10)	-0.35**	(0.15)
Blue-Collar Occ. Tenure	0.04	(0.12)	0.21	(0.18)
Homemaker Occ. Tenure	0.25	(0.16)	0.30	(0.23)
Other Occ. tenure	0.53***	(0.14)	0.13	(0.19)
< H.S. Degree	0.35***	(0.12)	-0.27	(0.18)
> H.S. Degree	-0.03	(0.11)	0.08	(0.16)
H.H. Income (log)	-0.14*	(0.07)	-0.08	(0.09)
H.H. Assets (log)	-0.12***	(0.02)	0.07**	(0.03)
Mother >= 8 yrs. Education	-0.15	(0.12)	0.13	(0.18)
Father > = 8 yrs. Education	-0.21†	(0.12)	-0.17	(0.17)
Father White-Collar Occ. Tenure	-0.08	(0.12)	0.02	(0.17)
R-Squared	0.13		0.09	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 14. Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Diggle-Kenward Selection Model

	Word-Recall			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	8.21***	(0.18)	-6.21***	(0.41)
Latent Predictor Variables				
Intercept Word-Recall				
Intercept Functional Limitations			-0.18***	(0.06)
Observed Predictor Variables				
Age	-0.23***	(0.01)	-0.22***	(0.02)
Black	-0.94***	(0.16)	0.45	(0.34)
Hispanic	-0.91***	(0.24)	0.82†	(0.48)
Female	1.15***	(0.12)	0.25	(0.27)
Married	-0.52***	(0.12)	0.34	(0.24)
Blue-Collar Occ. Tenure	-0.63***	(0.14)	0.54*	(0.28)
Homemaker Occ. Tenure	-0.65***	(0.19)	0.13	(0.38)
Other Occ. tenure	-0.21	(0.15)	0.09	(0.31)
< H.S. Degree	-0.74***	(0.14)	-0.09	(0.27)
> H.S. Degree	0.39***	(0.13)	-0.05	(0.26)
H.H. Income (log)	0.23***	(0.08)	0.09	(0.13)
H.H. Assets (log)	0.10***	(0.02)	0.00	(0.04)
Mother >= 8 yrs. Education	0.34**	(0.14)	-0.17	(0.27)
Father > = 8 yrs. Education	-0.03	(0.13)	0.00	(0.27)
Father White-Collar Occ. Tenure	0.29*	(0.13)	0.00	(0.27)
R-Squared	0.37		0.13	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 14 (Continued). Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Diggle-Kenward Selection Model

	Functional Limitations			
	Intercept		Intercept	
	b	*SE*	*b*	*SE*
Intercepts	2.33***	(0.15)	7.07***	(0.56)
Latent Predictor Variables				
Intercept Word-Recall			-0.22***	(0.05)
Intercept Functional Limitations				
Observed Predictor Variables				
Age	0.08***	(0.01)	0.19***	(0.02)
Black	-0.12	(0.16)	-0.17	(0.27)
Hispanic	-0.68***	(0.22)	-0.52***	(0.20)
Female	0.74***	(0.11)	-0.44**	(0.17)
Married	0.17	(0.11)	0.11	(0.21)
Blue-Collar Occ. Tenure	0.02	(0.12)	0.10	(0.27)
Homemaker Occ. Tenure	0.26	(0.17)	0.12	(0.22)
Other Occ. tenure	0.52***	(0.14)	-0.10	(0.40)
< H.S. Degree	0.36***	(0.12)	-0.29	(0.21)
> H.S. Degree	-0.01	(0.11)	0.15	(0.19)
H.H. Income (log)	-0.14*	(0.07)	-0.16	(0.11)
H.H. Assets (log)	-0.12***	(0.02)	0.05	(0.03)
Mother >= 8 yrs. Education	-0.14	(0.12)	0.29	(0.21)
Father > = 8 yrs. Education	-0.21†	(0.12)	-0.20	(0.21)
Father White-Collar Occ. Tenure	-0.09	(0.12)	0.08	(0.19)
R-Squared	0.13		0.21	

Note: N = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 15: Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Pattern-Mixture Model

	Word-Recall			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	9.10***	(0.19)	-2.65***	(0.29)
Latent Predictor Variables				
Intercept Word-Recall				
Intercept Functional Limitations			0.07	(0.04)
Observed Predictor Variables				
Age	-0.17***	(0.01)	-0.01	(0.02)
Black	-0.80***	(0.15)	-0.19	(0.26)
Hispanic	-1.03***	(0.23)	0.43	(0.36)
Female	0.92***	(0.11)	-0.66***	(0.20)
Married	-0.41***	(0.12)	0.16	(0.18)
Blue-Collar Occ. Tenure	-0.63***	(0.13)	0.53**	(0.21)
Homemaker Occ. Tenure	-0.57***	(0.18)	0.10	(0.29)
Other Occ. tenure	-0.18	(0.14)	0.14	(0.23)
< H.S. Degree	-0.58***	(0.13)	-0.08	(0.21)
> H.S. Degree	0.41***	(0.13)	0.07	(0.20)
H.H. Income (log)	0.16*	(0.07)	-0.07	(0.10)
H.H. Assets (log)	0.07***	(0.02)	-0.04	(0.03)
Mother >= 8 yrs. Education	0.32**	(0.13)	-0.07	(0.21)
Father > = 8 yrs. Education	-0.05	(0.13)	-0.06	(0.20)
Father White-Collar Occ. Tenure	0.26*	(0.13)	0.05	(0.20)
R-Squared	-[a]		-[a]	

Note: N = 4,653; † p < .10, * p < .05, ** p < .01, *** p < .001.; [a] standardized estimates necessary for calculation of R-square unavailable with categorical predictor variables unavailable.

Table 15 (Continued): Maximum Likelihood Estimates of Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Pattern-Mixture Model

	Functional Limitations			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	1.56***	(0.16)	3.88***	(0.43)
Latent Predictor Variables				
Intercept Word-Recall			-0.13***	(0.04)
Intercept Functional Limitations				
Observed Predictor Variables				
Age	0.03***	(0.01)	0.07***	(0.02)
Black	-0.15	(0.16)	0.10	(0.24)
Hispanic	-0.57***	(0.21)	0.14	(0.35)
Female	0.95***	(0.10)	-0.04	(0.16)
Married	0.14	(0.10)	-0.32*	(0.14)
Blue-Collar Occ. Tenure	0.05	(0.12)	0.16	(0.18)
Homemaker Occ. Tenure	0.26	(0.16)	0.30	(0.23)
Other Occ. tenure	0.52***	(0.13)	0.10	(0.19)
< H.S. Degree	0.29**	(0.12)	-0.29	(0.18)
> H.S. Degree	-0.02	(0.11)	0.13	(0.16)
H.H. Income (log)	-0.09	(0.06)	-0.08	(0.09)
H.H. Assets (log)	-0.10***	(0.02)	0.07***	(0.03)
Mother >= 8 yrs. Education	-0.18	(0.12)	0.15	(0.18)
Father > = 8 yrs. Education	-0.19†	(0.11)	-0.16	(0.17)
Father White-Collar Occ. Tenure	-0.08	(0.11)	0.03	(0.17)
R-Squared	-[a]		-[a]	

Note: *N* = 4,653; † $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.; [a] standardized estimates necessary for calculation of R-square unavailable with categorical predictor variables unavailable.

Table 16. Maximum Likelihood Estimates of Interactive and Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Data Missing at Random Model

	Word-Recall			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	8.12***	(0.17)	-2.94***	(0.28)
Latent Predictor Variables				
Intercept Word-Recall				
Intercept Functional Limitations			0.09*	(0.04)
Observed Predictor Variables				
Age	-0.22***	(0.01)	-0.03	(0.02)
Black	-0.82***	(0.16)	0.00	(0.27)
Hispanic	-0.94***	(0.23)	0.54	(0.37)
Female	1.12***	(0.12)	-0.70***	(0.20)
Married	-0.44***	(0.12)	0.23	(0.19)
Blue-Collar Occ. Tenure	-0.64***	(0.14)	0.53**	(0.22)
Homemaker Occ. Tenure	-0.63***	(0.18)	0.10	(0.29)
Other Occ. tenure	-0.20	(0.15)	0.09	(0.24)
< H.S. Degree	-0.67***	(0.13)	-0.05	(0.22)
> H.S. Degree	0.41***	(0.13)	0.09	(0.21)
H.H. Income (log)	0.22***	(0.08)	0.06	(0.12)
H.H. Assets (log)	0.10***	(0.02)	-0.03	(0.03)
Mother >= 8 yrs. Education	0.33**	(0.13)	-0.09	(0.21)
Father > = 8 yrs. Education	-0.04	(0.13)	-0.04	(0.21)
Father White-Collar Occ. Tenure	0.27*	(0.13)	0.06	(0.21)
*Latent * Observed Interactions*				
Intercept Word-Recall * Female				
Intercept Functional Limitations * HH inc.			-0.07**	(0.03)

Note: N = 4,653; † p < .10, * p < .05, **p < .01, *** p < .001.; [a] standardized estimates necessary for calculation of R-square unavailable with categorical predictor variables unavailable.

Table 16 (Continued). Maximum Likelihood Estimates of Interactive and Main Effects of Structural Paths and Predictor Variables on Trajectories of Word-Recall and Functional Limitations for Data Missing at Random Model

	Word-Recall			
	Intercept		Slope	
	b	*SE*	*b*	*SE*
Intercepts	2.41***	(0.15)	4.69***	(0.54)
Latent Predictor Variables				
Intercept Word-Recall			-0.20***	(0.06)
Intercept Functional Limitations				
Observed Predictor Variables				
Age	0.08***	(0.01)	0.10***	(0.02)
Black	-0.15	(0.16)	0.05	(0.24)
Hispanic	-0.66***	(0.22)	0.19	(0.35)
Female	0.76***	(0.11)	-1.50***	(0.56)
Married	0.14	(0.10)	-0.36**	(0.15)
Blue-Collar Occ. Tenure	0.04	(0.12)	0.18	(0.18)
Homemaker Occ. Tenure	0.25	(0.16)	0.34	(0.23)
Other Occ. tenure	0.53***	(0.14)	0.13	(0.19)
< H.S. Degree	0.35***	(0.12)	-0.28	(0.18)
> H.S. Degree	-0.03	(0.11)	0.10	(0.16)
H.H. Income (log)	-0.13*	(0.07)	-0.08	(0.09)
H.H. Assets (log)	-0.12***	(0.02)	0.07**	(0.03)
Mother >= 8 yrs. Education	-0.15	(0.12)	0.14	(0.18)
Father > = 8 yrs. Education	-0.21†	(0.12)	-0.19	(0.17)
Father White-Collar Occ. Tenure	-0.08	(0.12)	0.01	(0.17)
*Latent * Observed Interactions*				
Intercept Word-Recall * Female			0.16***	(0.06)
Intercept Functional Limitations * HH inc.				

Note: N = 4,653; † p < .10, * p < .05, ** p < .01, *** p < .001.; [a] standardized estimates necessary for calculation of R-square unavailable with categorical predictor variables unavailable.

Figure 1. Path Diagram of Latent Growth Model

Cognitive outcome variable represented by y0 – y4. Note: Unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

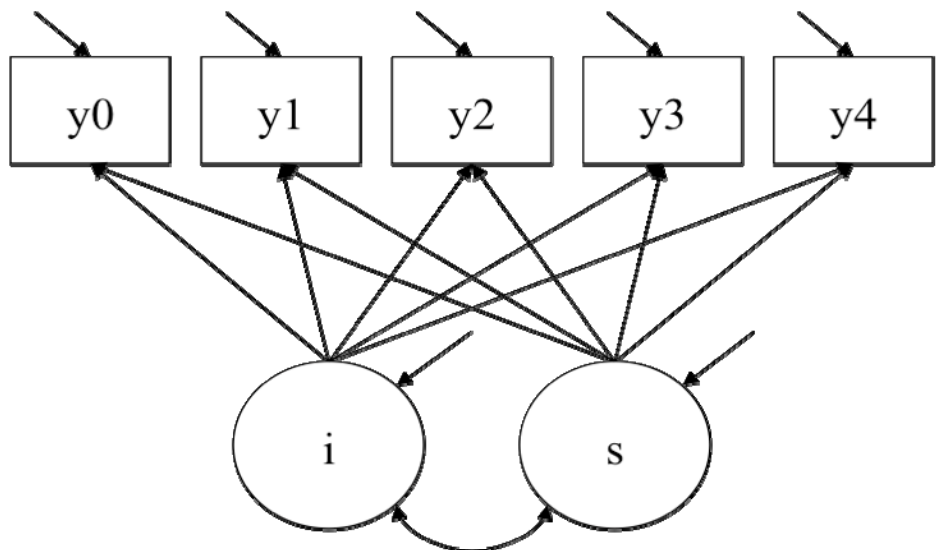

Figure 2. Path Diagram of Diggle-Kenward Latent Growth Model

Cognitive outcome variable represented by y0 – y4. Discrete-time dropout indicators for cognitive outcome represented by d1 - d4. Note: Dashed paths indicate logistic regression; unit factor loadings (latent variable loadings) are omitted to reduce clutter.

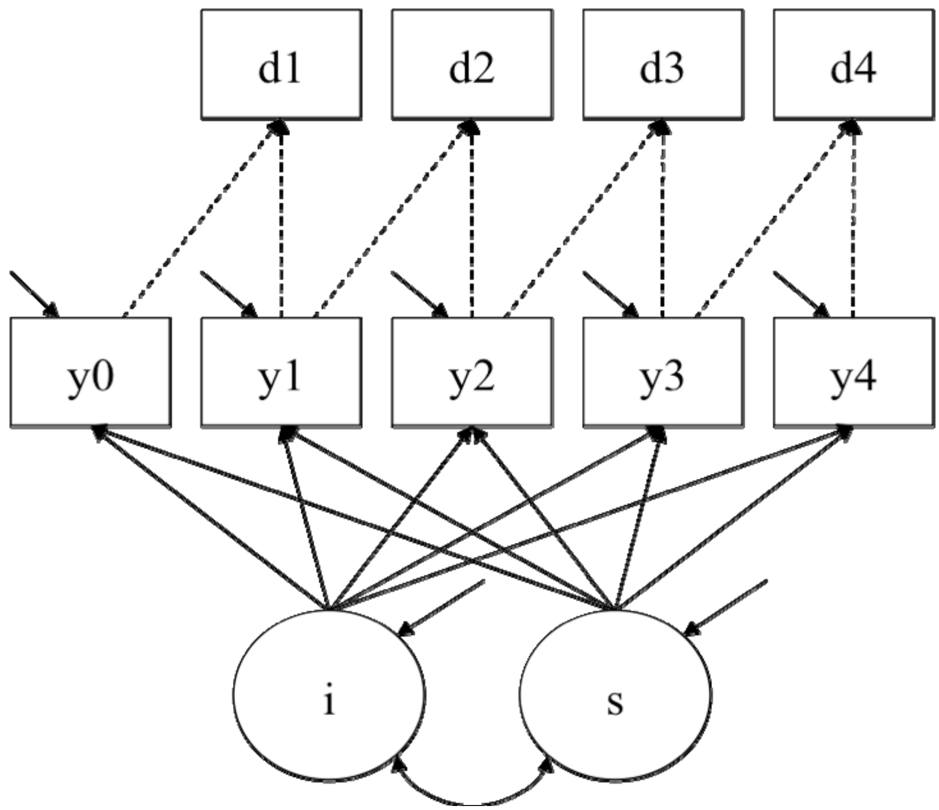

Figure 3. Path Diagram of Wu-Carroll Latent Growth Model

Cognitive outcome variable represented by y0 – y4. Discrete-time dropout indicators for cognitive outcome represented by d1 - d4. Note: Dashed paths indicate logistic regression; unit factor loadings (latent variable loadings) are omitted to reduce clutter.

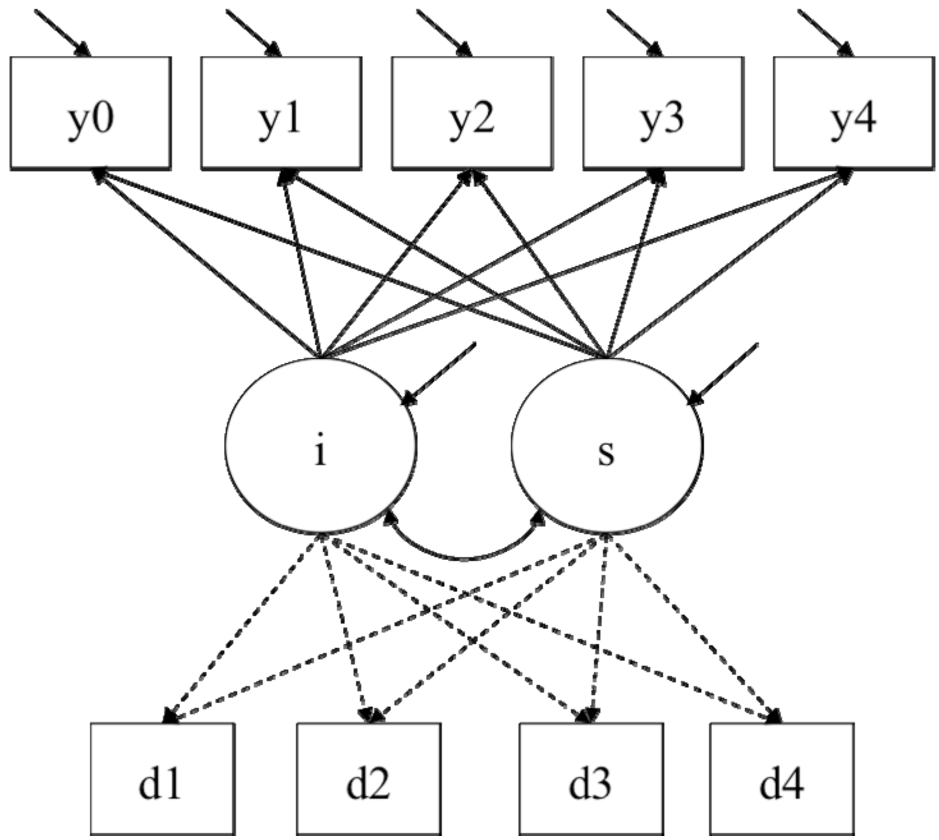

Figure 4. Path diagram of Pattern Mixture Latent Growth Model

Cognitive outcome variable represented by y0 – y4. Dropout dummy indicators for cognitive outcome represented by d1 - d4. Note: unit factor loadings (latent variable loadings) are omitted to reduce clutter.

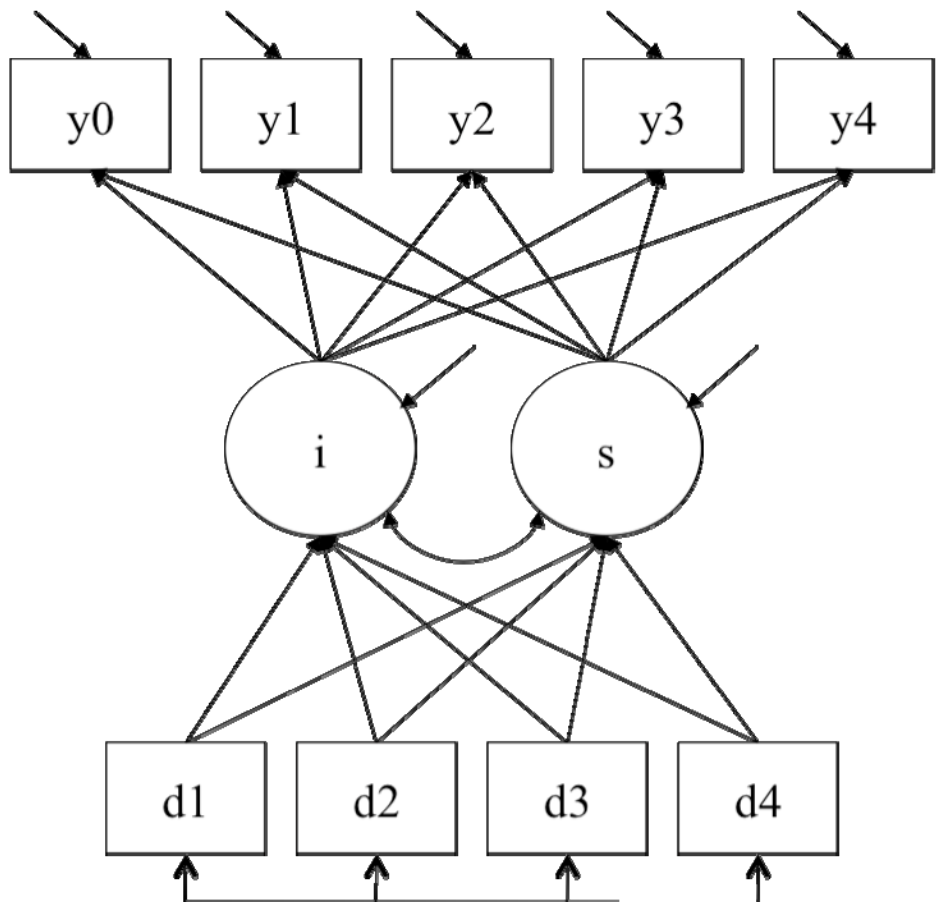

Figure 5. Estimated Word-Recall Trajectories from Missing at Random and Not Missing at Random Latent Growth Models

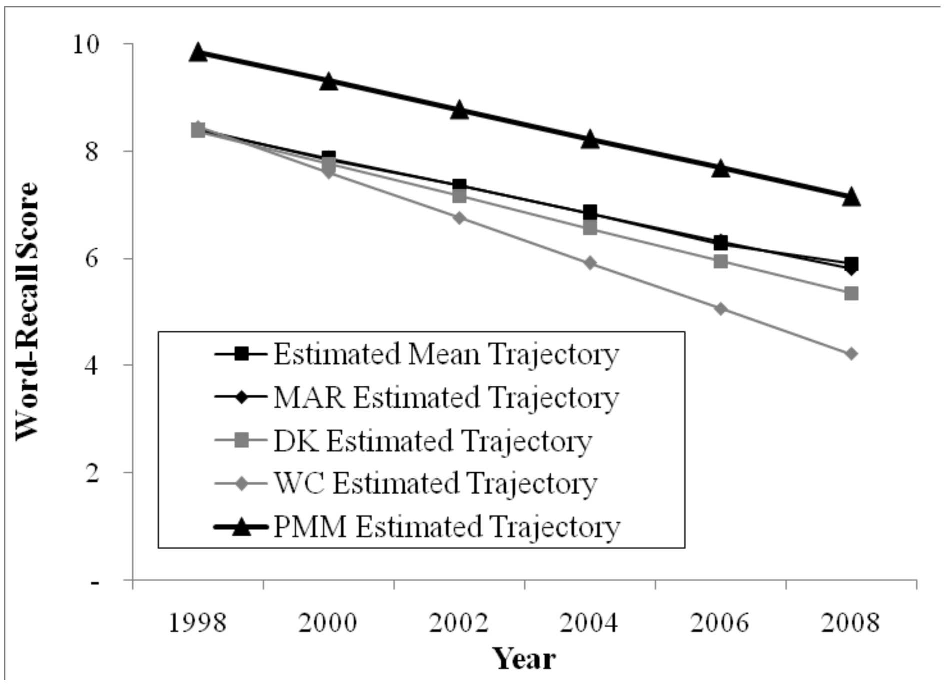

Figure 6. Estimated Word-Recall Trajectories for Missing at Random and Not Missing at Random Latent Growth Models for Whites

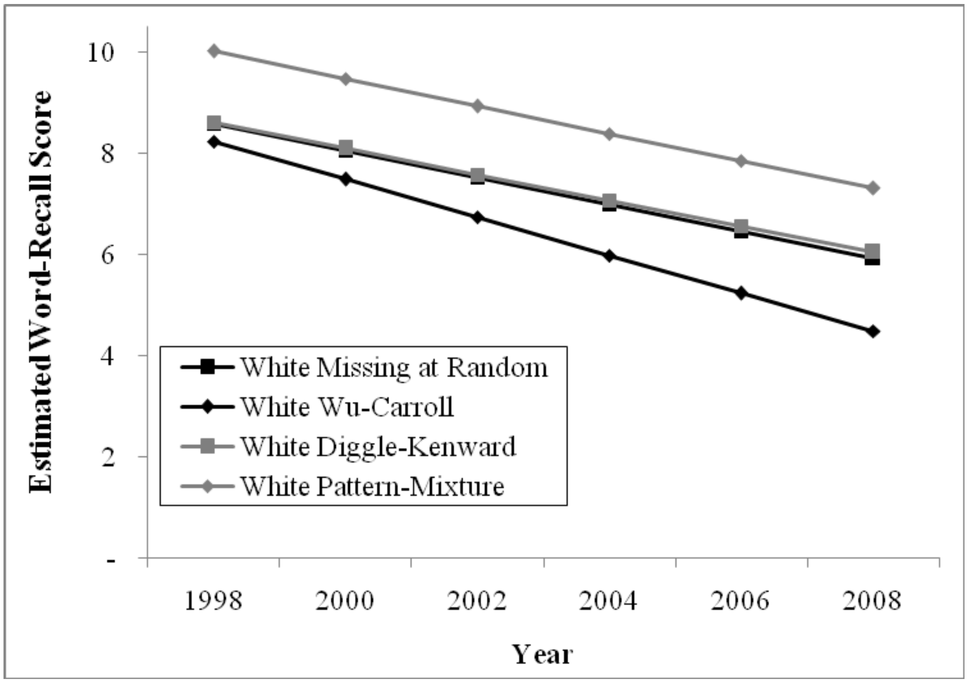

Figure 7. Estimated Word-Recall Trajectories for Missing at Random and Not Missing at Random Latent Growth Models for Blacks

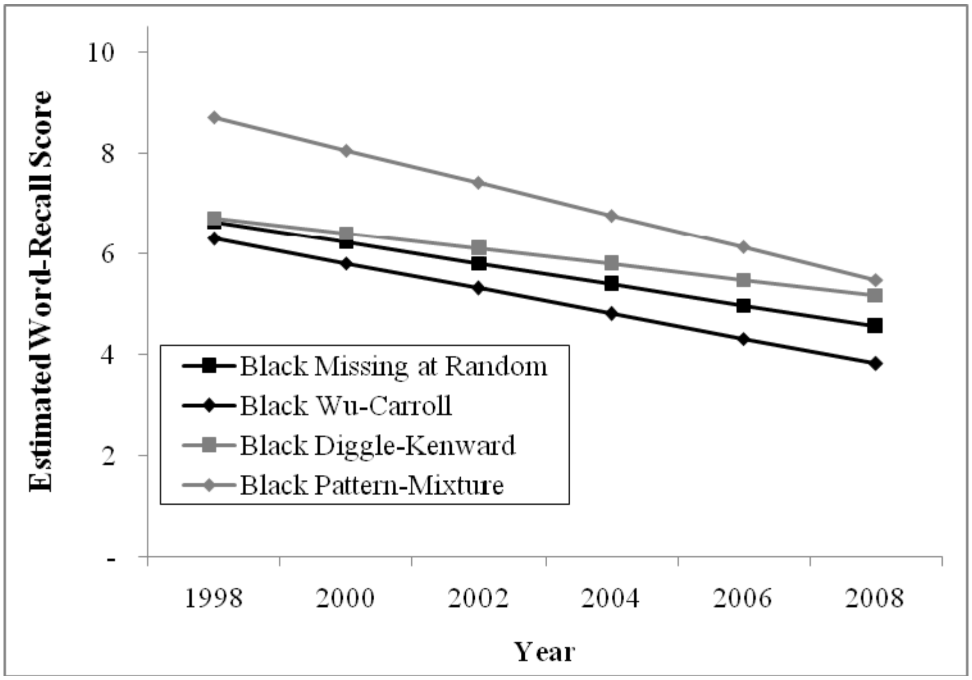

Figure 8. Missing at Random Model Estimates for Black Baseline Word-Recall Scores by Household Assets and Diabetes

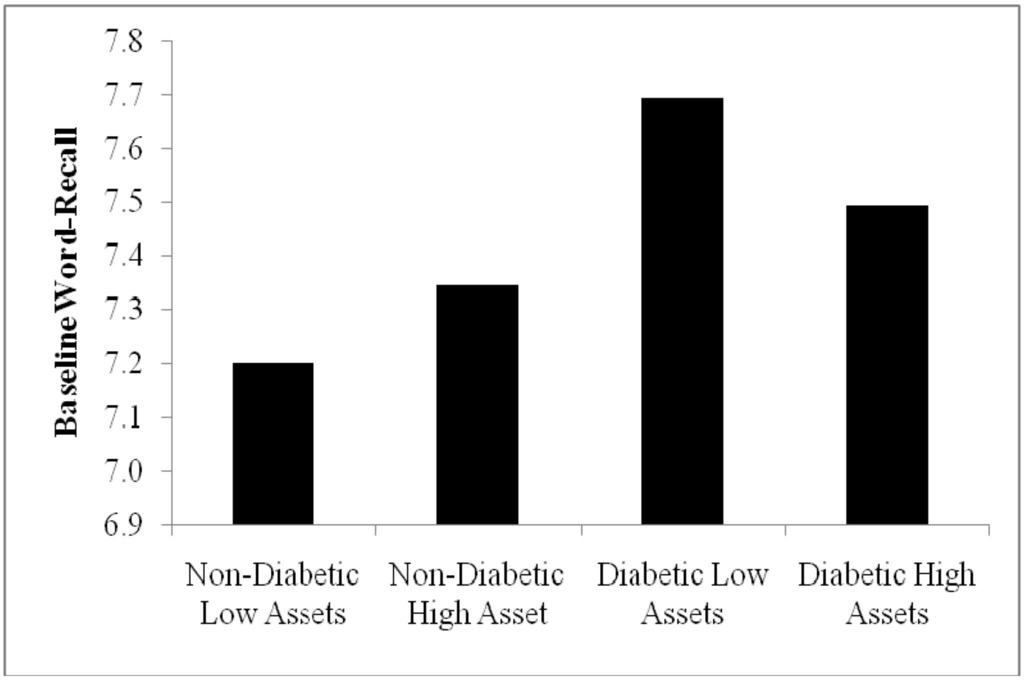

Figure 9. Missing at Random Model Estimates for Black Baseline Word-Recall Scores by Household Assets and Diabetes Diagnosis

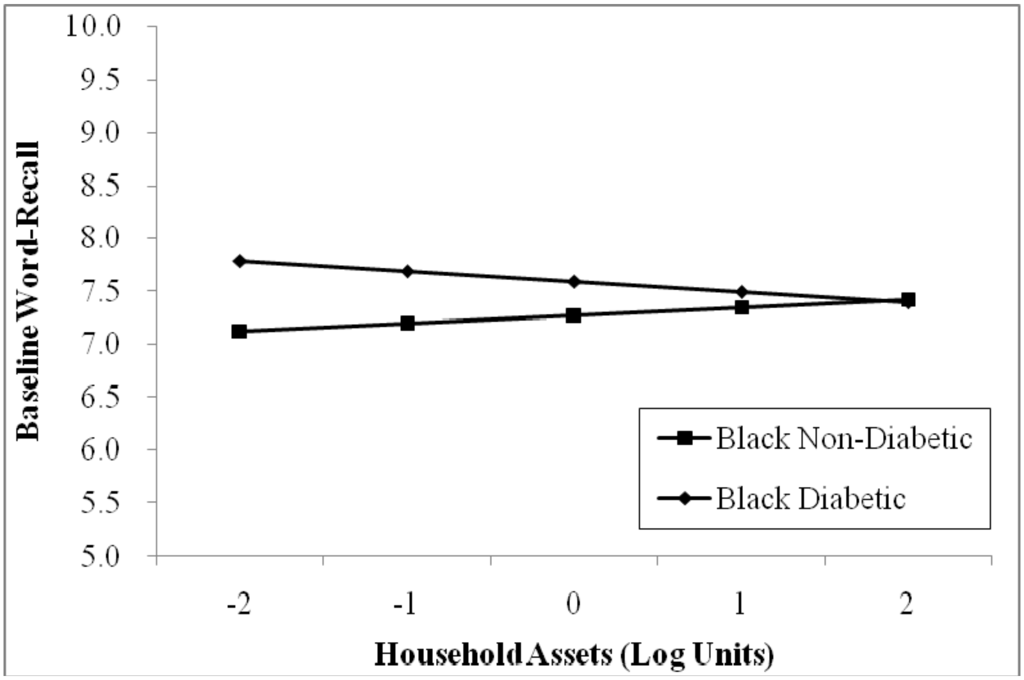

Figure 10. Missing at Random Model Estimates for Black Word-Recall Score Trajectories by Longest Occupational Tenure and Diabetes Diagnoses

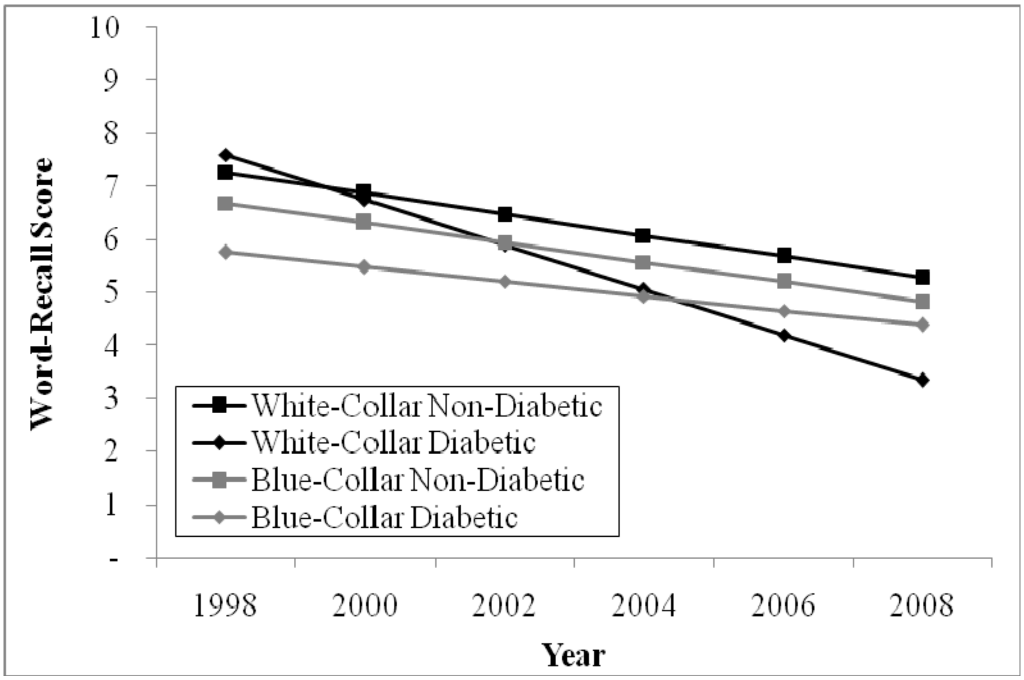

Figure 11. Parallel Process Structural Model Development

Model 1 represents structural model with no causal structure including correlations within process, between intercepts for each process, and between slopes for each process. Model 2 adds a casual path from word-recall intercept to functional limitation slope to Model 1. Model 3 adds a causal path from functional limitation intercept to word-recall slope to Model 1. Model 4 represents the final structural model that includes causal paths from the intercept of each process to the slope of the alternate process.

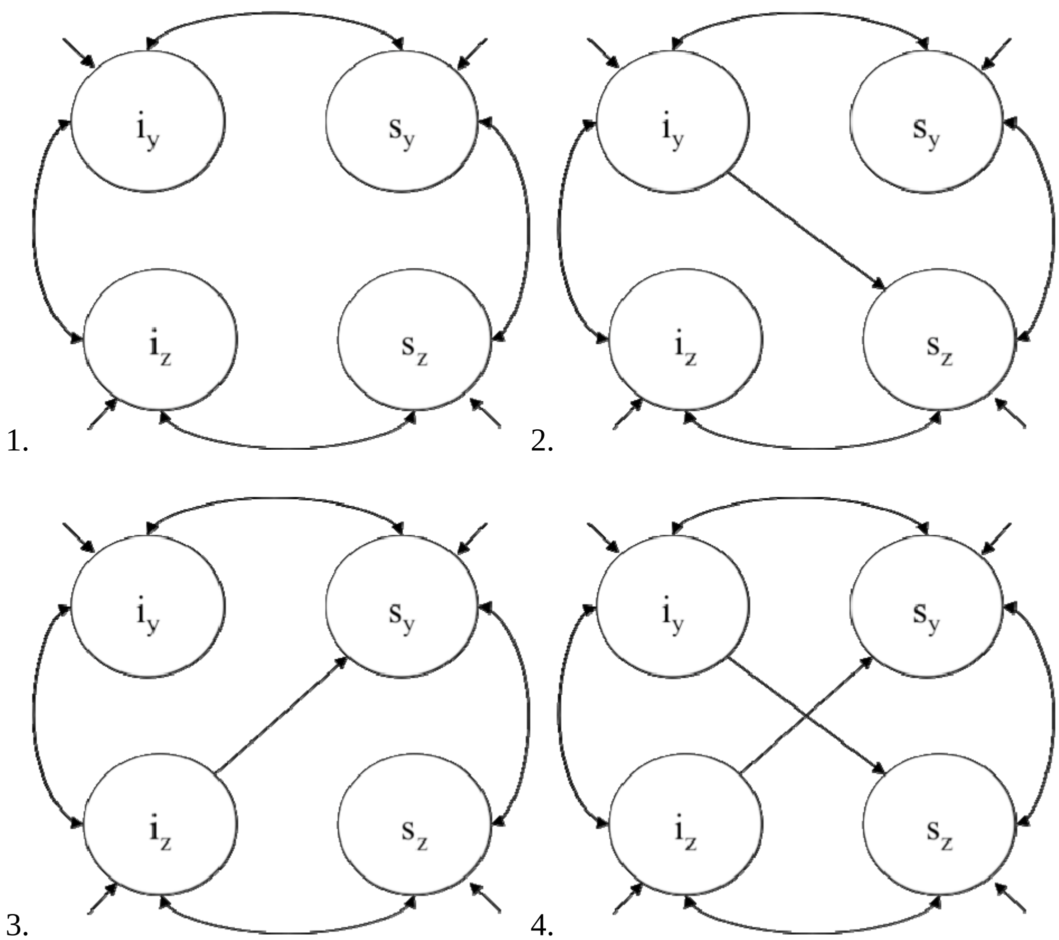

Figure 12. Conditional Parallel Process Strucutral Model with Interactions between Latent and Observed Variables

Random intercept and slope word-recall represented by i_y, s_y. Random intercept and slope functional limitations represented by i_z, s_z. Observed predictor variables are represented by x_i.

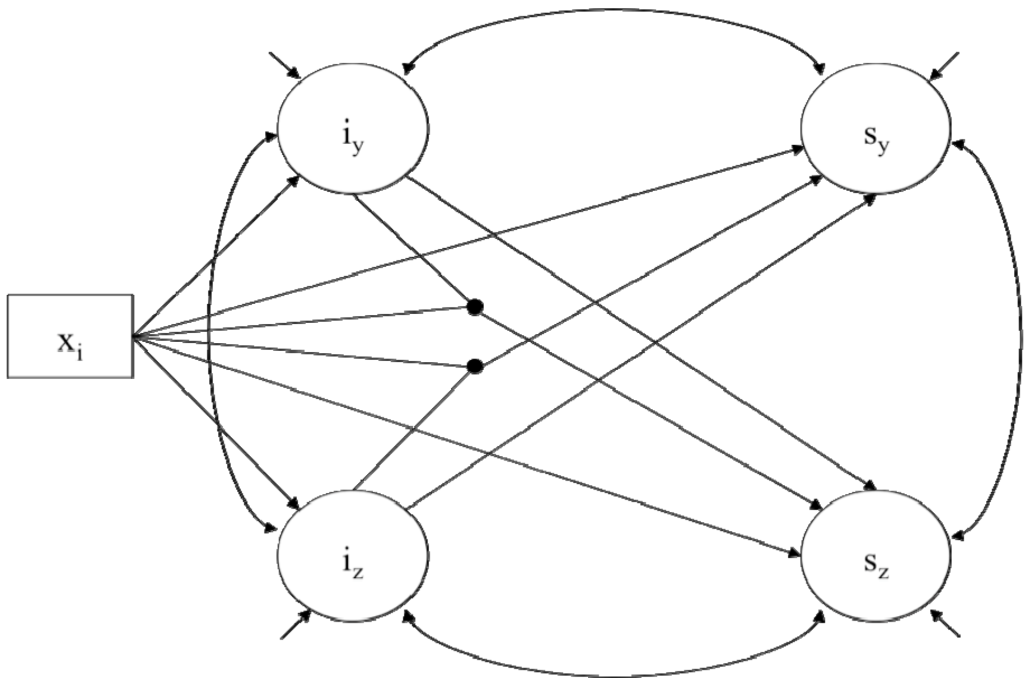

Figure 13. Parallel Process Growth Curve Measurement Model

y0 – y4: cognitive outcome variable; z0 – z4: functional limitations variable; i_y, s_y: random intercept and slope word-recall; i_z, s_z: random intercept and slope functional limitations; d0-d4: dropout indicators. Note: Unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

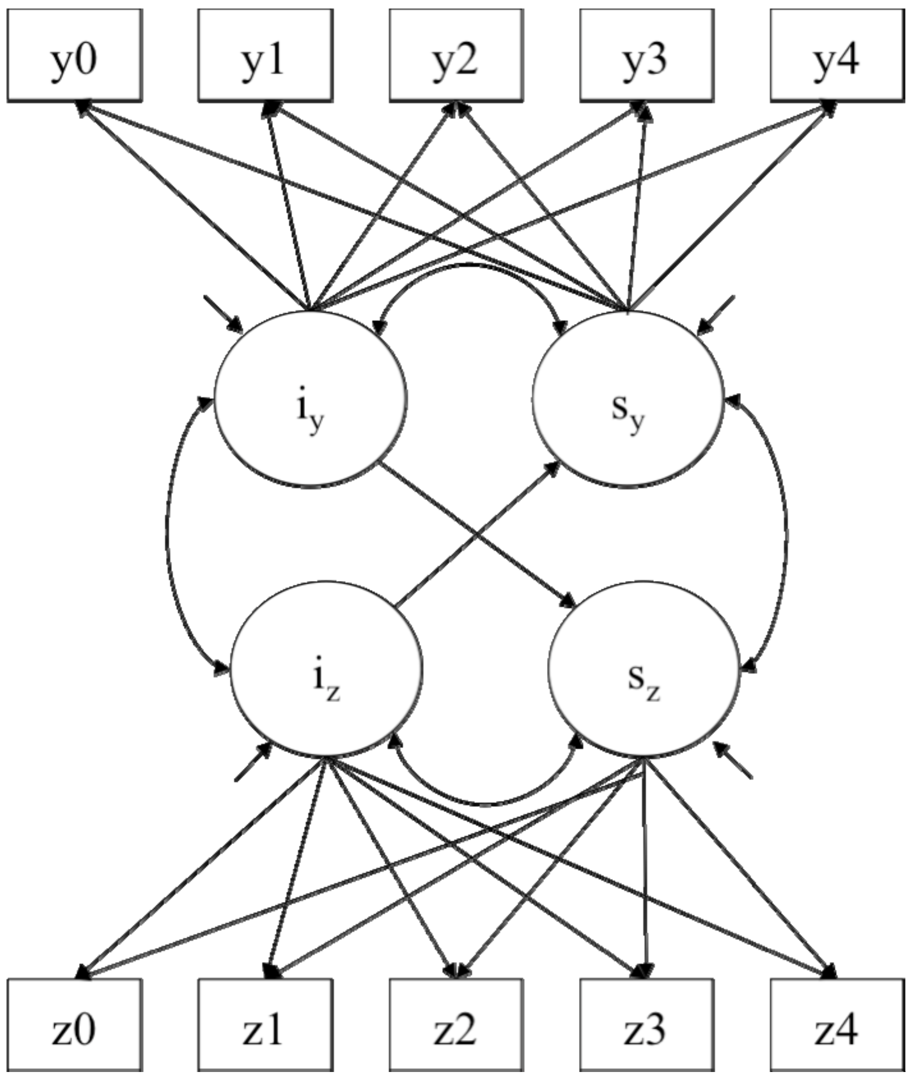

Figure 14. Parallel Process Growth Curve Measurement Model with Diggle-Kenward Selection Model

Observed functional limitations represented by z0 – z4. Random intercept and slope word-recall represented by i_y, s_y. Random intercept and slope functional limitations represented by i_z, s_z. Discrete-time dropout indicators for each process represented by d_y1 - d_y4 and d_z1 - d_z4. Note: Dashed paths indicate logistic regression; unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

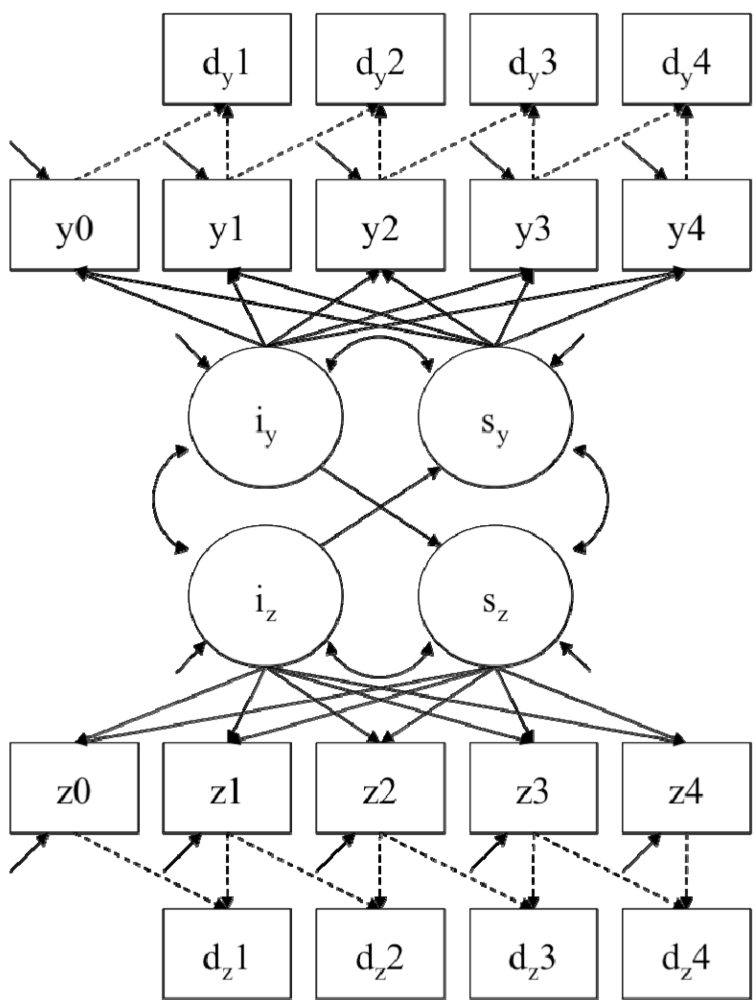

Figure 15. Parallel Process Growth Measurement Model with Pattern Mixture Model

Observed cognitive outcome variable represented by y0 – y4. Observed functional limitations represented by z0 – z4. Random intercept and slope word-recall represented by i_y, $s_{y.}$ Random intercept and slope functional limitations represented by i_z, s_z. Dropout dummy indicators for each process represented by d_y1 - d_y4 and d_z1 - d_z4. Note: Unit factor loadings (latent variable loadings) and random error terms are omitted to reduce clutter.

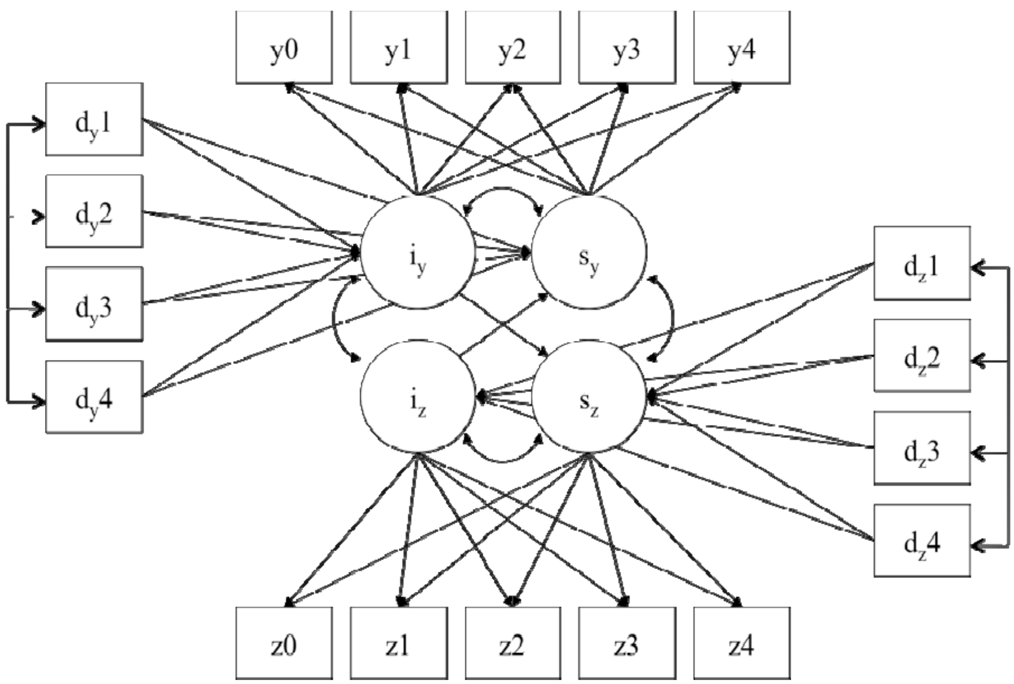

Figure 16. Regression Point Estimates and 95% Confidence Intervals for Functional Limitations Slope on Initial Word-Recall by Gender

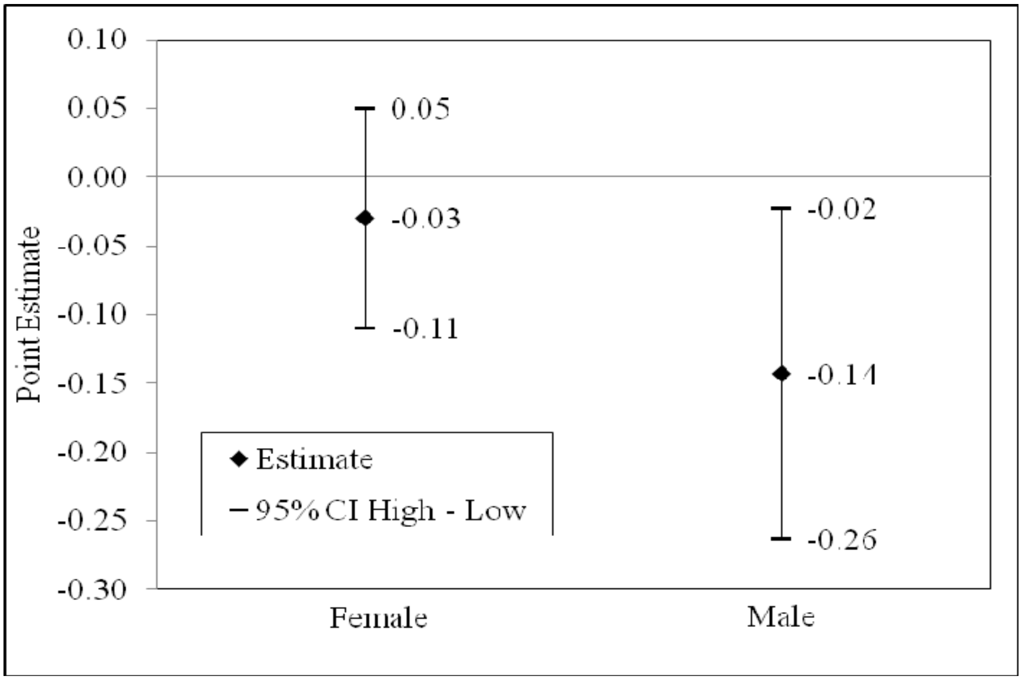

Figure 17. Regression Point Estimates and 95% Confidence Intervals for Word-Recall Slope on Initial Functional Limitations by Household Income